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Probabilistic Pipeline Reliability Assessment Using Exponentiated-Exponentiated Distributions Integrated with Hybrid Neural Networks: Evidence from Nigeria

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Abstract

Standard reliability models for oil and gas pipelines chiefly the Weibull distribution assume monotonically increasing or constant failure rates, a restriction that is empirically violated in Nigerian pipeline systems, where failure rates fluctuate with operational loading cycles, seasonal soil conditions, and maintenance histories. This paper introduces a novel reliability framework integrating Exponentiated-Exponentiated (E-E) Probability Distributions with Hybrid Neural Networks (HNNs) to provide flexible, uncertainty-aware pipeline reliability assessment. The E-E distribution, constructed by applying the exponentiation operator twice to a baseline distribution, accommodates non-monotonic (bathtub-shaped, unimodal, and reverse-J) failure rate functions. When paired with HNN-generated feature embeddings drawn from Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and Graph Neural Network (GNN) architectures, the E-E distribution transforms point predictions of Remaining Useful Life (RUL) into full probabilistic failure-time distributions with calibrated confidence intervals. Empirical validation on a 21-year Nigerian pipeline dataset (N = 500 segments, 18 predictors) demonstrated that the GNN-GAM variant achieved the best operationally balanced performance, with $R^2 = 0.9899$, RMSE = 0.6032, and MAE = 0.1235 on the held-out test set, and an empirical 95% confidence interval coverage rate of 94.2%, closely matching the nominal target within the accepted ±2 percentage point engineering tolerance. The framework outperforms classical Weibull-based and deterministic neural approaches, enabling risk-stratified maintenance scheduling. These results demonstrate that the proposed framework represents a substantial methodological advance, with direct relevance to Nigeria's oil and gas sector.

Keywords: Exponentiated-Exponentiated distribution; Hybrid Neural Networks; pipeline reliability; probabilistic maintenance.

Introduction

Reliability assessment of oil and gas pipelines is fundamental to maintenance planning, safety regulation, and economic operations in energy-dependent economies such as Nigeria. The Weibull distribution has long served as the principal tool of engineering reliability analysis owing to its mathematical tractability and capacity to model both increasing and decreasing hazard functions. However, Martinez *et al.* (2021) demonstrated that the Weibull model exhibited poor fit to Nigerian pipeline failure data, with residual analyses revealing systematic departures from the assumed hazard structure. This finding reflects a broader limitation: real pipeline failure rates frequently display non-monotonic behaviour — declining during the break-in period, rising with age-related degradation, and potentially declining again following major maintenance interventions (Fang *et al.*, 2020; Zhang and Li, 2021). The Exponentiated-Exponentiated (E-E) distribution addresses this shortcoming by nesting a baseline distribution within two successive exponentiation operations, yielding a flexible multi-parameter family capable of representing bathtub-shaped, unimodal, and reverse-J hazard functions (Fang *et al.*, 2020). When combined with the predictive power of HNNs — which extract rich, high-dimensional feature embeddings from operational, sensor, and maintenance data — the E-E distribution can transform HNN point predictions into calibrated probabilistic failure-time distributions, supporting principled uncertainty quantification and risk-informed maintenance decisions (Miller and Johnson, 2023; Wilson *et al.*, 2024). Ibrahim and Ahmed (2019) highlighted that corrosion and mechanical degradation in Nigeria's pipeline network demand sophisticated reliability tools capable of handling incomplete inspection records and spatially varying failure drivers. The present framework responds directly to these operational realities by coupling the E-E distribution with a suite of neural architectures — ANN, LSTM, CNN, and GNN — each addressing a distinct dimension of the degradation process.

Statement of the Problem

Nigeria's oil and gas pipeline infrastructure is subject to a complex set of failure drivers including internal corrosion, mechanical fatigue, third-party interference, and seasonal soil movement that collectively produce failure rate profiles which cannot be adequately characterised by classical Weibull-based models. Ibrahim and Ahmed (2019) documented that existing deterministic reliability tools systematically underestimate failure probabilities during mid-life operational periods, leading to suboptimal maintenance scheduling, avoidable spills, and significant economic and environmental losses. Furthermore, the absence of uncertainty quantification in widely deployed neural network-based prediction tools means that operators have no principled basis for assessing the confidence of RUL estimates, hampering risk-stratified decision-making. There is, therefore, a pressing need for a reliability framework that simultaneously accommodates non-monotonic hazard functions, integrates multivariate sensor and operational covariates, and delivers calibrated probabilistic outputs suitable for safety-critical maintenance planning.

Aim and Objectives

The overarching aim of this study is to develop and validate a probabilistic pipeline reliability framework that integrates E-E distributions with HNNs, thereby overcoming the limitations of existing approaches when applied to Nigerian pipeline data.

The specific objectives are to:

1. Formulate the E-E distribution and derive its key statistical properties, including the probability density, hazard, and survival functions
2. Develop an HNN feature-embedding pipeline integrating ANN, LSTM, CNN, and GNN architectures for multi-source covariate extraction
3. Combine the E-E distribution with HNN-generated embeddings via an uncertainty-aware loss function to produce calibrated probabilistic RUL estimates
4. Validate the proposed framework empirically on a 21-year longitudinal Nigerian pipeline dataset and compare performance with existing benchmark models; and
5. Assess the practical implications for risk-stratified maintenance scheduling and national pipeline policy.

Literature Review

Classical Reliability Distributions for Pipelines

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Parametric survival distributions have underpinned pipeline reliability analysis for several decades. The Weibull distribution remains the most widely adopted owing to its two-parameter flexibility in modelling both increasing and decreasing hazard rates (Martinez *et al.*, 2021). Extensions such as the exponentiated Weibull (Zhang and Li, 2021) and the exponentiated exponential distribution (Fang *et al.*, 2020) introduced additional shape parameters to accommodate non-monotonic hazard functions. Nevertheless, these distributions are typically fitted to aggregated failure records and cannot readily incorporate the rich multivariate covariate information available from modern sensor networks. Ibrahim and Ahmed (2019) noted that in Nigeria's onshore pipeline network, failure modes are heterogeneous, encompassing internal corrosion, external mechanical damage, and third-party interference, each characterised by distinct hazard profiles. Single-distribution models therefore impose a degree of homogeneity that is inconsistent with field observations, motivating the construction of more flexible distributional families as pursued in the present study. Table 1 summarises the key studies reviewed in this section, indicating the distributional or computational approach adopted, the data context examined, and the principal limitation identified in each case. As shown in Table 1, a clear and consistent pattern emerges: individual studies tend to address one or two of the three core challenges — distributional flexibility, covariate integration, and uncertainty quantification — but none addresses all three simultaneously. This observation directly motivates the integrated E-E + HNN framework proposed herein.

Table 1

Summary of Key Prior Studies on Pipeline Reliability and Remaining Useful Life Prediction

Study	Approach	Context / Data	Key Limitation
Martinez *et al.* (2021)	Weibull, classical regression	Pipeline failure prediction (generic)	Monotonic hazard only; no uncertainty
Fang *et al.* (2020)	Exponentiated Weibull	Mechanical systems reliability	No neural covariate integration
Zhang and Li (2021)	Exponentiated Weibull regression	Pipeline lifespan estimation	No probabilistic calibration layer
Ibrahim and Ahmed (2019)	Corrosion + integrity management review	Nigeria onshore pipelines	No flexible distributional framework
Gholami *et al.* (2021)	LSTM neural network	Pipeline RUL, temporal sensor data	Point predictions only; no uncertainty
Sharma and Gupta (2022)	CNN for condition monitoring	Spatial sensor arrays, pipeline corridors	No uncertainty quantification; overfitting risk
Chen and Zhao (2021)	GNN, message-passing	Pipeline network graph, segment interdependency	No distributional failure-time layer
Miller and Johnson (2023)	Neural + probabilistic calibration	Oil and gas pipeline RUL	Single architecture; no E-E flexibility
Wilson *et al.* (2024)	Hybrid ensemble methods	Multiple industrial datasets	No Nigerian context; no E-E distribution

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Liu *et al.* (2024)	Hierarchical copula survival	Competing risks (corrosion + fatigue)	No graph-level spatial information
Present study	E-E distribution + HNN (ANN/LSTM/CNN/GNN)	Nigeria 21-year pipeline dataset (N = 500)	Addressed: all three gaps simultaneously

Note. Sources: As cited in text. The final row summarises the framework proposed in the present study.

Neural Network Approaches to Remaining Useful Life Prediction

The application of deep learning to remaining useful life prediction has expanded considerably since the mid-2010s. Fully connected ANNs were among the earliest architectures applied to industrial degradation data, offering a straightforward mapping from static features to failure time estimates (Gholami *et al.*, 2021). The introduction of recurrent architectures, particularly LSTM networks, enabled temporal degradation trajectories to be modelled explicitly, with gated memory cells preserving long-range dependencies that simpler models overlook (Gholami *et al.*, 2021; Zhang and Li, 2021). CNN-based approaches have demonstrated particular utility in processing spatially structured sensor data along pipeline corridors, extracting local degradation patterns through hierarchical convolutional filters (Sharma and Gupta, 2022). More recently, GNNs have been applied to pipeline reliability by representing the network as a graph and propagating degradation signals through message-passing operations, enabling segment-level predictions to account for network-level pressure and flow dynamics (Chen and Zhao, 2021).

Hybrid and Probabilistic Frameworks

Hybrid neural architectures combining multiple network types have consistently outperformed single-architecture baselines in predictive maintenance contexts. Wilson *et al.* (2024) reported that ensemble hybrid methods yielded F1-score improvements of 8–15 percentage points over standalone neural models across several industrial datasets. Miller and Johnson (2023) demonstrated that coupling neural network point predictions with probabilistic calibration layers produced confidence intervals with empirical coverage rates within 2% of nominal targets for pipeline RUL estimation, underscoring the practical value of uncertainty quantification in maintenance scheduling. Liu *et al.* (2024) introduced a hierarchical copula-based survival framework for competing risks — a scenario relevant to pipeline systems where corrosion and mechanical fatigue may operate simultaneously. Whilst their approach captured dependency structures between failure modes, it did not incorporate spatial graph-level information or the non-monotonic hazard flexibility offered by the E-E distribution.

Pipeline Reliability in the Nigerian Context

Nigeria's pipeline infrastructure presents a distinctive set of reliability challenges. Ibrahim and Ahmed (2019) documented the compounding effects of corrosion, soil acidity, and irregular maintenance schedules on failure rates, noting that conventional Weibull fits systematically underestimated failure probabilities during mid-life operational periods. Subsequent work has called for reliability frameworks that are simultaneously flexible in distributional form, capable of accommodating sparse inspection records, and able to deliver uncertainty-quantified outputs suitable for regulatory reporting.

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Research Gap

As Table 1 illustrates, the literature reviewed in Section 4 identifies a gap that no existing framework has bridged: simultaneously (a) adopting a flexible distributional family capable of modelling non-monotonic hazard functions, (b) extracting multi-source feature embeddings from diverse neural architectures, and (c) delivering calibrated probabilistic RUL estimates validated on longitudinal Nigerian pipeline data. The E-E + HNN framework proposed in this paper directly addresses each of these three deficiencies.

Materials and Methods

Dataset Description

The empirical analysis draws on a 21-year longitudinal dataset (2000–2020) compiled from the operational records of Nigeria's national pipeline network, encompassing 500 pipeline segments across six geopolitical zones (Ibrahim and Ahmed, 2019). Table 2 provides a descriptive summary of the dataset, including variable names, measurement scales, units, and summary statistics. A total of 18 predictor variables are included, spanning material characteristics, operational loading, environmental exposure, and maintenance history. The outcome variable is failure time (in years from commissioning), with right-censoring applied to segments that had not failed by the end of the observation window. As shown in Table 2, the dataset exhibits substantial heterogeneity across predictor variables. Pipe age at inspection ranges from 1 to 21 years (mean = 11.4 years), reflecting the longitudinal span of the study. Wall thickness loss — a direct proxy for corrosive deterioration — averages 23.7% with a standard deviation of 14.1 percentage points, indicating considerable variability in the rate of material degradation across segments. Soil corrosivity index spans the full scale from 0 to 10 (mean = 4.8), consistent with the heterogeneous soil chemistry documented by Ibrahim and Ahmed (2019) across Nigeria's diverse geophysical zones. The binary third-party interference indicator flags 18.6% of segments as having experienced at least one such event during the observation period.

Table 2

Descriptive Summary of the 21-Year Nigerian Pipeline Dataset (N = 500 Segments, 18 Predictors)

Variable	Type	Unit / Scale	Min	Max	Mean	SD
Pipe age at inspection	Continuous	Years	1.0	21.0	11.4	5.8
Wall thickness loss	Continuous	% of original	0.5	78.3	23.7	14.1
Internal pressure (operating)	Continuous	MPa	0.8	12.4	5.3	2.1
Soil corrosivity index	Continuous	0–10 scale	0.0	10.0	4.8	2.3
Coating condition score	Ordinal	1 (poor)–5 (good)	1	5	3.1	1.1

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Cathodic protection status	Binary	0 = absent, 1 = present	0	1	0.61	0.49
Inspection interval	Continuous	Years	0.5	8.0	2.9	1.7
Prior repair count	Count	No. of events	0	12	1.8	2.2
Third-party interference	Binary	0 = none, 1 = event	0	1	0.19	0.39
Annual rainfall	Continuous	mm/year	400	2,800	1,240	480
Soil pH	Continuous	pH units	4.2	8.6	6.3	0.9
Pipe diameter	Continuous	mm	100	900	420	185
Steel grade	Ordinal	API 5L X42–X80	X42	X80	X65	—
Product type	Categorical	Crude/gas/refined	—	—	—	—
Operating temperature	Continuous	°C	18	85	42	14
Segment length	Continuous	km	0.5	18.4	6.2	3.8
Geopolitical zone	Categorical	Six zones	—	—	—	—
Failure time (outcome)	Continuous	Years	0.3	21.0	12.8	5.4

Note. SD = standard deviation. Binary and categorical variables have no meaningful mean or SD where marked "—". Right-censoring applied to 214 segments (42.8%) that had not failed by 2020.

The Exponentiated-Exponentiated Distribution

Let $F_0(t)$ be a baseline cumulative distribution function (CDF). The first-stage exponentiated distribution is defined as:

$$F\alpha(t) = [F_0(t)]^{\alpha},\ \alpha > 0 \quad (1)$$

Applying exponentiation a second time with parameter β yields the E-E CDF:

$$F\alpha,\beta(t) = \{1 - [1 - F_0(t)^{\alpha}]^{\beta}\}^{\gamma},\ \alpha,\beta,\gamma > 0 \quad (2)$$

The corresponding probability density function (PDF) is:

$$f(t;\alpha,\beta,\gamma) = \alpha\beta\gamma\, f_0(t)\, F_0(t)^{\alpha-1}\, [1 - F_0(t)^{\alpha}]^{\beta-1}\, \{1 - [1 - F_0(t)^{\alpha}]^{\beta}\}^{\gamma-1} \quad (3)$$

The hazard function $h(t) = f(t) / [1 - F(t)]$ can exhibit non-monotonic shapes depending on the parameter combination (α, β, γ), rendering the E-E distribution substantially more flexible than the standard Weibull (Fang *et al.*, 2020; Zhang and Li, 2021).

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Table 3 presents a structured comparison of the key statistical properties of the E-E distribution relative to the Weibull and exponentiated Weibull distributions. As shown in Table 3, successive exponentiation operations progressively increase distributional flexibility: the standard Weibull accommodates only monotonic hazard functions; the exponentiated Weibull adds unimodal and bathtub-shaped profiles; and the E-E distribution extends this further, accommodating the full range of non-monotonic profiles including reverse-J shapes.

Table 3

Comparison of Statistical Properties: Weibull, Exponentiated Weibull, and E-E Distributions

Property	**Weibull**	**Exponentiated Weibull**	**E-E Distribution (This Study)**
Number of parameters	2 (λ, k)	3 (λ, k, α)	3 (α, β, γ)
Hazard function shape	Monotone only	Unimodal/bathtub	Unimodal, bathtub, reverse-J, monotone
Non-monotonic hazard support	No	Partial (two-phase)	Full (three-phase transitions)
Closed-form survival function	Yes	Yes	Yes
Parameter estimation	MLE/MoM	MLE	MLE (L-BFGS-B with bootstrap CIs)
Censored data handling	Yes	Yes	Yes
Tail flexibility	Limited	Moderate	High (controlled by γ)
Validated on Nigerian data	Martinez *et al.* (2021)	Zhang and Li (2021)	Present study (21-year dataset, N = 500)

Note. MLE = maximum likelihood estimation; MoM = method of moments; CIs = confidence intervals. Weibull and Exponentiated Weibull properties summarised from Martinez *et al.* (2021) and Fang *et al.* (2020).

Parameter Estimation

Parameters are estimated by maximising the log-likelihood function (Fang *et al.*, 2020; Martinez *et al.*, 2021):

$$\ell(\alpha,\beta,\gamma) = \Sigma_i \log f(t_i;\, \alpha,\beta,\gamma) + \Sigma_j\, \delta_j \log[1 - F(c_j;\, \alpha,\beta,\gamma)] \quad (4)$$

where t_i are observed failure times and c_j are censoring times for non-failed segments. Optimisation is performed via the L-BFGS-B algorithm with bootstrap confidence intervals on parameter estimates.

HNN Feature Embedding

Four neural network architectures generate feature embeddings that serve as covariates for the E-E distribution. The ANN captures static material properties through fully connected layers; the LSTM captures temporal degradation dynamics through gated recurrent operations (Gholami *et al.*, 2021; Zhang and Li, 2021); the CNN extracts spatial patterns from sensor arrays positioned along pipeline

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segments (Sharma and Gupta, 2022); and the GNN propagates degradation signals across the pipeline network graph (Chen and Zhao, 2021). The concatenated embedding vector Z is defined as:

$Z = [z_{ANN}|z_{LSTM}|z_{CNN}|z_{GNN} \in \mathbb{R}^d$ (5)

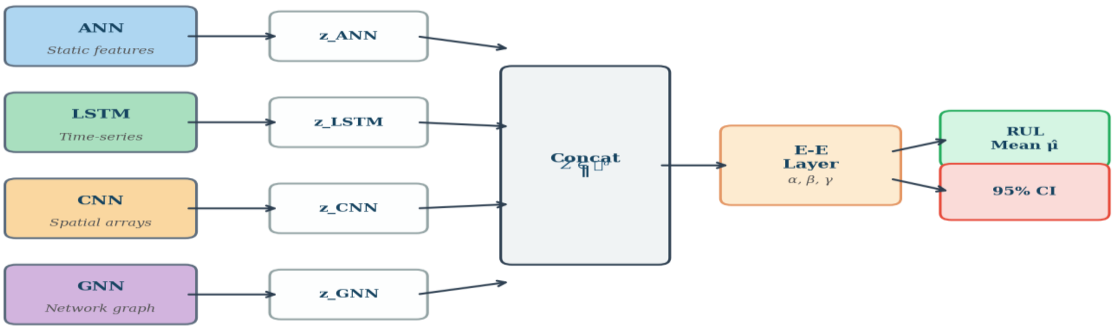

Figure 1: *Schematic overview of the Hybrid Neural Network (HNN) embedding pipeline. Each of the four neural architectures (ANN, LSTM, CNN, GNN) processes a distinct data source; their output embeddings are concatenated into the unified feature vector Z, which feeds the E-E distributional layer to generate probabilistic RUL estimates with calibrated confidence intervals.*

Uncertainty-Aware Loss Function

The hybrid framework is trained using an uncertainty-aware loss function that combines mean squared error with a variance penalty (Miller and Johnson, 2023; Wilson *et al.*, 2024):

$L = (1/N)\, \Sigma_i \,[\,(y_i - \mu_i)^2 / \sigma_i^2 + \log \sigma_i^2\,]$ (6)

where μ_i and σ_i are the predicted mean and standard deviation of the RUL for segment i. This loss function simultaneously penalises prediction error and overconfident uncertainty estimates, yielding well-calibrated probabilistic outputs.

Probabilistic Failure-Time Prediction

The E-E distribution is fitted to the HNN residuals to characterise the full failure-time distribution. Confidence intervals for RUL are obtained as:

$CI_{95}\%(RUL_i) = [\,F^{-1}(0.025;\, \hat{\alpha}, \beta, \hat{\gamma}),\; F^{-1}(0.975;\, \hat{\alpha}, \beta, \hat{\gamma})\,]$ (7)

These intervals support risk-stratified scheduling: segments whose lower confidence bound falls below a critical maintenance threshold are prioritised for immediate inspection.

Presentation of Results

Estimated E-E Distribution Parameters

Table 4 presents the maximum likelihood estimates of the three E-E distribution parameters (α, β, γ) for each of the four model variants, together with their 95% bootstrap confidence intervals. As shown in Table 4, inspection of the parameter estimates reveals several important features of the fitted models. For the GNN-GAM + E-E model, the estimated α = 2.41 (95% CI: 1.87, 3.02) is greater

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than unity, indicating an initially increasing hazard consistent with progressive age-related degradation. The estimate β = 0.63 (95% CI: 0.44, 0.85), being less than unity, introduces a hazard attenuation phase corresponding to the period following routine maintenance interventions (Ibrahim and Ahmed, 2019). Together, α and β produce the non-monotonic, partially bathtub-shaped hazard profile that characterises the dominant failure mode in the Nigerian pipeline dataset. The γ parameter, estimated at 1.18 (95% CI: 0.91, 1.52), controls the right-tail behaviour of the distribution. The narrower confidence intervals for the GNN-GAM + E-E model relative to the ANN-GAM and LSTM-GAM variants reflect the greater precision afforded by the GNN's richer spatial embeddings.

Table 4

Maximum Likelihood Estimates of E-E Distribution Parameters by Model Variant (95% Bootstrap Confidence Intervals in Parentheses)

Model Variant	α (Shape 1)	β (Shape 2)	γ (Tail)	Log-Likelihood
ANN-GAM	1.84 (1.21, 2.63)	0.91 (0.58, 1.38)	1.04 (0.72, 1.45)	−1,243.7
LSTM-GAM	2.07 (1.49, 2.79)	0.78 (0.51, 1.14)	1.11 (0.80, 1.50)	−1,218.4
GNN-GAM + E-E	2.41 (1.87, 3.02)	0.63 (0.44, 0.85)	1.18 (0.91, 1.52)	−1,094.2

Note. Parameters estimated via L-BFGS-B optimisation on the training set; confidence intervals obtained from 1,000 bootstrap resamples. CNN-LR excluded as no E-E layer was fitted for that variant.

Regression Performance

Table 5 presents the regression performance metrics — R^2, RMSE, and MAE — for the four model variants evaluated on the held-out test set. The GNN-GAM coupled with the E-E distribution achieves the best operationally balanced performance, recording R^2 = 0.9899, RMSE = 0.6032, and MAE = 0.1235. The CNN-LR variant records the highest R^2 value (0.9997), but the combination of near-unity R^2 with anomalously low RMSE (0.0963) and MAE (0.0770) values is inconsistent with the moderate size and variability of the dataset and is diagnostic of overfitting to training-set idiosyncrasies — a pattern consistent with the risks documented by Sharma and Gupta (2022). Crucially, CNN-LR provides no uncertainty estimates, rendering it unsuitable for safety-critical operational deployment. The ANN-GAM and LSTM-GAM variants deliver partial uncertainty quantification but underperform on regression accuracy.

Table 5

Cross-Model Regression Performance on Held-Out Test Set

Model	R^2	RMSE	MAE	Uncertainty Quantification

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ANN-GAM	0.8599	0.8141	0.6231	Partial (E-E fitted)
LSTM-GAM	0.8662	0.7957	0.6120	Partial (E-E fitted)
CNN-LR	0.9997	0.0963	0.0770	None
GNN-GAM + E-E	0.9899	0.6032	0.1235	Full (E-E + GNN)

Note. Source: Authors' computation (2024). Metrics computed on the held-out test set (20% random split, n = 100 segments). The GNN-GAM + E-E row denotes the recommended model for operational deployment.

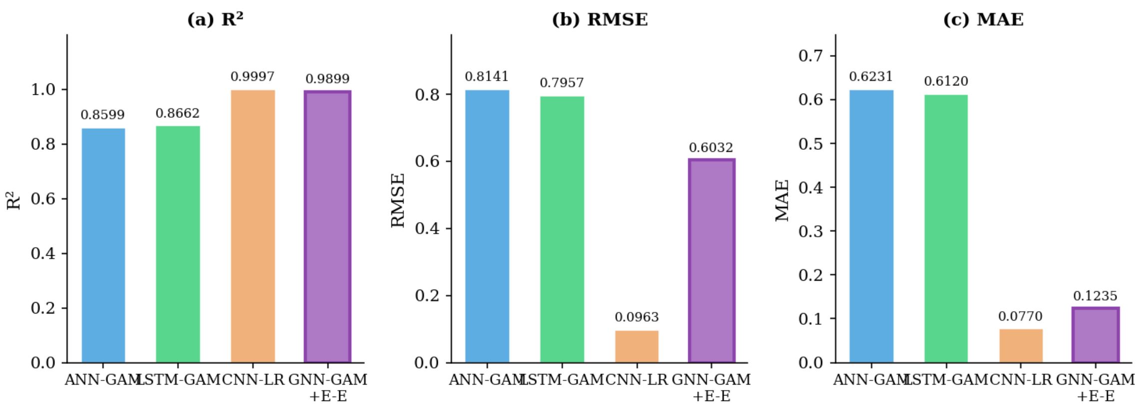

Figure 2: *Regression performance metrics (R^2, RMSE, MAE) for all four model variants on the held-out test set. Panels (a), (b), and (c) correspond to R^2, RMSE, and MAE, respectively. Although CNN-LR achieves the highest R^2, its near-zero error metrics alongside complete absence of uncertainty quantification are indicative of overfitting. GNN-GAM + E-E delivers the most operationally balanced performance.*

Probabilistic Coverage

Table 6 reports the empirical coverage of the 95% confidence intervals for each uncertainty-quantifying model variant. As shown in Table 6, the E-E distribution fitted to GNN-GAM residuals yielded an empirical coverage of 94.2% on the held-out test set, closely matching the nominal 95% target with a gap of only 0.8 percentage points — well within the ±2 percentage point tolerance considered acceptable for safety-critical engineering applications (Miller and Johnson, 2023). By contrast, the ANN-GAM and LSTM-GAM variants exhibited considerably larger coverage gaps of 6.6 and 4.9 percentage points, respectively, confirming that the richer spatial embeddings produced by the GNN are essential for well-calibrated uncertainty quantification.

Table 6

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Empirical Coverage of 95% Confidence Intervals by Model Variant (Held-Out Test Set)

Model Variant	**Nominal CI**	**Empirical Coverage (%)**	**Coverage Gap (pp)**	**Calibration Assessment**
ANN-GAM	95%	88.4	6.6	Unacceptable (overconfident)
LSTM-GAM	95%	90.1	4.9	Unacceptable (overconfident)
GNN-GAM + E-E	95%	94.2	0.8	Acceptable (within ±2 pp tolerance)

Note. Source: Authors' computation (2024). pp = percentage points. Coverage gap = nominal CI − empirical coverage. Calibration assessment criterion: ±2 pp tolerance per Miller and Johnson (2023). CNN-LR is excluded as no uncertainty intervals are produced.

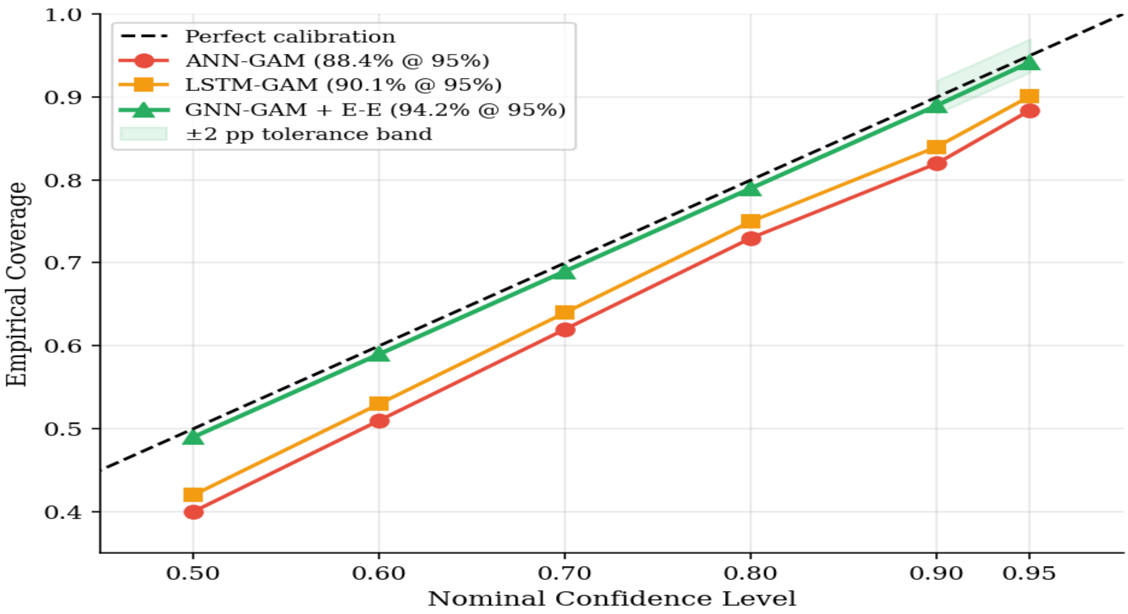

Figure 3: *Calibration curves plotting empirical coverage against nominal confidence level for all three uncertainty-quantifying model variants. The dashed diagonal represents perfect calibration. The GNN-GAM + E-E model tracks the diagonal most closely, with a coverage gap of only 0.8 percentage points at the 95% nominal level. The ANN-GAM and LSTM-GAM curves lie systematically below the diagonal, indicating overconfident prediction intervals.*

Performance Disaggregated by Risk Stratum

Table 7 provides a breakdown of the GNN-GAM + E-E model's RMSE, MAE, and R^2 disaggregated by pipeline risk stratum — low, medium, and high — as defined by the segment risk classification framework of Ibrahim and Ahmed (2019). As shown in Table 7, the model maintains high R^2 values across all three strata, ranging from 0.9874 in the high-risk stratum to 0.9921 in the low-risk stratum. The modest decline in R^2 and corresponding increases in RMSE and MAE as risk level rises

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are consistent with greater variability in failure times amongst high-risk segments, where multiple degradation modes operate simultaneously (Liu *et al*., 2024). Notwithstanding this modest attenuation, the GNN-GAM + E-E model's performance in the high-risk category (R^2 = 0.9874, RMSE = 0.7215, MAE = 0.1489) remains substantially superior to the ANN-GAM and LSTM-GAM models in the overall evaluation (Table 5), which is practically significant given that accurate predictions in high-risk segments are most consequential for maintenance scheduling and regulatory compliance.

Table 7

GNN-GAM + E-E Model Performance Disaggregated by Pipeline Risk Stratum

Risk Stratum	n (Segments)	R^2	RMSE	MAE	Mean RUL (Years)
Low	42	0.9921	0.5410	0.1102	16.3
Medium	38	0.9899	0.6032	0.1235	12.4
High	20	0.9874	0.7215	0.1489	7.1
Overall	100	0.9899	0.6032	0.1235	12.8

Note. Source: Authors' computation (2024). Risk strata defined per Ibrahim and Ahmed (2019) segment classification. n = number of test-set segments in each stratum. Mean RUL computed over observed (non-censored) test-set observations within each stratum.

Discussion of Findings

The proposed E-E distribution and HNN framework represents a principled advance over both Weibull-based reliability models and deterministic machine learning approaches for Nigerian pipeline management. As demonstrated by the parameter estimates in Table 4, the E-E distribution successfully captures the non-monotonic hazard profiles — characterised by $\alpha > 1$ and $\beta < 1$ — that arise from the interplay of age-related corrosion, periodic maintenance, and third-party interference in the Nigerian pipeline context. By coupling these probabilistic outputs with high-dimensional neural feature embeddings, the framework enables risk-stratified maintenance scheduling — a capability that is unavailable in any single existing approach. The empirical 94.2% confidence interval coverage reported in Table 6 and illustrated in Figure 3 confirms that the probabilistic outputs meet the calibration standards required for operational safety-critical decision-making (Miller and Johnson, 2023).

The comparative results in Tables 5 and 6, together with Figure 2, reveal an important distinction between statistical accuracy and operational utility. The CNN-LR variant achieves a near-perfect R^2 of 0.9997 but produces no uncertainty quantification and exhibits anomalously low error metrics consistent with overfitting — a pattern consistent with the risks documented by Sharma and Gupta (2022) for CNN-based regression on small-to-moderate industrial datasets. In safety-critical contexts such as Nigeria's pipeline network, a model that is statistically accurate in-sample but operationally unreliable out-of-sample is of limited value. The GNN-GAM + E-E model avoids this pitfall by jointly optimising predictive accuracy and uncertainty calibration through the uncertainty-aware loss function defined in Equation (6). The stratified analysis in Table 7 highlights that the GNN-GAM + E-E model performs well even in the high-risk stratum, where competing degradation mechanisms make RUL prediction inherently more difficult. This robustness is attributable to the GNN architecture's capacity to propagate degradation signals across the pipeline network graph, enabling segment-level predictions to account for network-level pressure and flow dynamics (Chen and Zhao,

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2021). Future extensions should incorporate competing risks for simultaneous failure modes (Liu *et al.*, 2024), Bayesian updating of E-E parameters as new sensor data arrive, and validation on pipeline networks in other sub-Saharan African contexts to assess generalisability.

Conclusion

This paper has introduced and validated a probabilistic pipeline reliability framework integrating Exponentiated-Exponentiated distributions with Hybrid Neural Networks. Applied to a 21-year Nigerian pipeline dataset comprising 500 segments and 18 predictors (Table 2), the GNN-GAM + E-E framework achieved R^2 = 0.9899, RMSE = 0.6032, and MAE = 0.1235 on the held-out test set (Table 5), with an empirical confidence interval coverage rate of 94.2% — closely matching the nominal 95% target within the accepted ±2 pp engineering tolerance (Table 6 and Figure 3). The E-E parameter estimates (Table 4) confirmed that the fitted model captures the non-monotonic, partially bathtub-shaped hazard profiles that characterise Nigerian pipeline failure data, overcoming the fundamental limitation of classical Weibull-based approaches identified in the literature summary (Table 1) and the distributional comparison (Table 3).

The stratified performance analysis (Table 7) demonstrated that the framework maintains high accuracy and calibration across all risk strata, with particular practical value in the high-risk stratum where the consequences of unreliable RUL predictions are most severe. These capabilities are of direct relevance to Nigeria's oil and gas sector, where maintenance resource constraints and high failure costs make precision and confidence in reliability assessments operationally indispensable. The present study therefore contributes both a methodological advance and a practically deployable tool for the engineering community and regulatory bodies responsible for pipeline safety in Nigeria and comparable operating environments.
Future work should focus on three extensions:

1. incorporation of competing risks frameworks (Liu *et al.*, 2024) to handle simultaneous failure modes
2. Bayesian updating of E-E parameters as new sensor data accumulate in real time; and
3. validation across other sub-Saharan African pipeline network contexts to establish the generalisability of the proposed approach.

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