Reliability and Uncertainty Quantification for Pipeline Systems Using Exponentiated-Exponentiated Distributions: A Case Study of Nigerian Oil and Gas Pipelines

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Abstract

This paper introduces a comprehensive framework for modelling the reliability of pipeline systems in Nigeria's oil and gas industry, utilizing the Exponentiated-Exponentiated (E-E) distribution. The E-E distribution, a generalization of the Exponentiated Weibull distribution, affords greater flexibility to model failure rates that may increase, decrease, or remain constant over time — a characteristic that renders it particularly suitable for capturing the non-monotonic degradation patterns commonly observed in pipeline systems. To enhance predictive accuracy and uncertainty quantification, the E-E distribution is integrated with hybrid neural-statistical models that combine Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN). The resulting model provides probabilistic predictions for pipeline lifespan and Remaining Useful Life (RUL), offering appreciable improvements in predictive maintenance capabilities. Real-world data from Nigeria's oil and gas pipelines are used to validate the model, demonstrating superior performance relative to traditional models such as the Weibull distribution and ARIMA. The study highlights the potential of this framework to enhance maintenance planning and decision-making, thereby improving pipeline operations across the Nigerian oil and gas sector.

Keywords: *Reliability Modelling, Exponentiated-Exponentiated (E-E) Distribution, Pipeline Degradation, Hybrid Models, Predictive Maintenance, Oil and Gas Sector*

1. Introduction

Pipeline infrastructure is vital for transporting oil, natural gas, and refined products across Nigeria. Corrosion, mechanical stress, and environmental degradation continually threaten these assets, giving rise to substantial operational and environmental risks (Osei *et al.*, 2020). Pipeline failures in Nigeria have led to environmental disasters and considerable financial losses (NEITI, 2023), making pipeline integrity management a matter of critical national importance. Recent reports from the Nigerian National Petroleum Corporation (NNPC) indicate that Nigeria loses approximately 250,000 barrels of oil per year owing to pipeline vandalism and failures (NNPC, 2020) — a statistic that underscores the urgent need for more robust prediction models capable of materially reducing the risks posed by pipeline degradation (Reuters, 2022).

Traditional reliability models, such as the Weibull and Log-Normal distributions, have been widely employed in predicting pipeline lifespan. However, these models often fail to capture the non-monotonic degradation patterns that are characteristic of real pipeline systems (Almalki and Nadarajah, 2014). The Exponentiated-Exponentiated (E-E) distribution was introduced by Adebayo and Bello (2021) as an extension of the Weibull model, offering substantially enhanced flexibility. The E-E model allows failure rates to increase, decrease, or remain constant over time, rendering it well suited to modelling the complex degradation patterns observed in pipelines subject to varying environmental conditions and maintenance interventions (Gusmão *et al.*, 2021). This paper examines how the E-E distribution can be combined with modern data analysis methods — including neural networks — to improve pipeline reliability prediction. Using actual monitoring data from Nigerian oil and gas pipelines, the study aims to provide actionable guidance for maintenance planning and risk reduction, thereby assisting operators in managing their pipeline assets more safely and efficiently. Table 1 summarizes the key descriptive statistics of the pipeline systems considered in this study.

Table 1

Pipeline system statistics

Pipeline ID	Pressure (Pa)	Temperature (°C)	Flow Rate (m³/s)	Corrosion Rate (mm/year)	Maintenance Events	Repair History (1=Yes, 0=No)	Soil Condition	Age (Years)
P010	397,749.84	51	24.96	0.3184	5	0	Poor	1
P007	377,694.51	46	20.42	0.2540	3	1	Good	6
P005	351,476.09	44	17.98	0.2173	4	0	Poor	10
P004	332,059.15	41	15.36	0.1648	4	0	Poor	13
P003	293,663.73	40	12.57	0.1291	2	0	Moderate	14

1.1 Aim and Objectives of the Study

The principal aim of this study is to model pipeline reliability by predicting failures and estimating the Remaining Useful Life (RUL) of pipeline segments, utilizing the Exponentiated-Exponentiated (E-E) distribution as the core statistical framework. This method is robust for modelling time-varying failure rates, and its capacity to represent non-monotonic degradation patterns where failure rates may increase, decrease, or remain constant owing to environmental wear or maintenance interventions provides a compelling advantage over conventional approaches. The specific objectives are to:

i. demonstrates the flexibility of the E-E distribution in capturing non-monotonic failure patterns in pipeline systems.
ii. integrate the E-E distribution with hybrid neural-statistical models to improve reliability estimation.
iii. validate the proposed model using real-world pipeline data from Nigeria's oil and gas industry.

2. Literature Review

Pipeline degradation and failure prediction have long been key research topics in reliability engineering. Traditionally, analysts have employed models such as the Weibull and log-normal distributions on account of their simplicity and capacity to capture a range of failure rate behaviours. The Weibull distribution can describe random, early-life, and wear-out failures through its shape parameter β: $\beta = 1$ implies a constant failure rate (equivalent to the exponential distribution); $\beta > 1$ yields an increasing rate indicative of wear-out; whilst $\beta < 1$ gives a decreasing rate typical of early failures (Smith *et al.*, 2021). Despite widespread adoption, the Weibull distribution is limited in its capacity to model non-monotonic failure rates. In real pipelines, degradation can follow complex patterns driven by environmental conditions, maintenance interventions, and material wear — a variability that the standard Weibull model cannot always accommodate fully (Zhang and Xie, 2020; Zhao and Guo, 2021).

To overcome these limitations, the Exponentiated Weibull (EW) distribution was developed, incorporating an additional exponentiation parameter (Mudholkar and Srivastava, 1993; Shittu and Adepoju, 2014). The EW distribution can model failure rates that increase, decrease, or remain constant over time (Adebayo and Bello, 2021; Mahmoudi and Sepahdar, 2012). Recognizing that pipeline failures are influenced by multiple interacting factors — including environmental stress, mechanical wear, and repair interventions (Onyenekwe *et al.*, 2021) — Adebayo and Bello (2021) developed the Exponentiated-Exponentiated (E-E) distribution as a further extension, capable of modelling degradation behaviour more accurately in systems where failure rates change in an irregular or non-monotonic manner over time (Akanji *et al.*, 2023; Adeyemi *et al.*, 2023).

In recent years, research has increasingly explored combining machine learning techniques with traditional reliability models to improve predictive maintenance in industrial systems. Liu *et al.*, (2021) demonstrated that hybrid neural networks can substantially improve the prediction of industrial machine failures. Zhang and Xie (2020) applied Long Short-Term Memory (LSTM) networks to predict pipeline RUL, though their models still relied on simpler Weibull and ARIMA formulations, constraining their ability to capture complex, non-linear failure patterns (Hassan *et al.*, 2022). More recently, Alobaidi *et al.*, (2022) proposed a semi-supervised learning framework for pipeline failure detection, whilst Wang *et al.*, (2024) demonstrated the merits of hybrid convolutional-LSTM architectures for RUL estimation in oil and gas pipelines. Messiah *et al.*, (2025) further confirmed the value of reliability-based corrosion rate prediction models for pipeline integrity management.

This study builds on earlier work by deploying the E-E distribution alongside advanced machine learning techniques to identify pipeline deterioration at an earlier stage. This approach enables maintenance teams to schedule repairs before issues escalate — a capability that is particularly valuable in Nigeria, where pipelines are exposed to harsh environmental conditions, ageing infrastructure, and inconsistent maintenance regimes (Shokrollahi *et al.*, 2017; Alhassan *et al.*, 2025).

2.1 Research Gap

Despite recent advances, significant challenges remain in predicting pipeline degradation and failure. Although the Weibull distribution is widely used in reliability analysis, it struggles to accommodate non-monotonic failure rates. Real pipeline systems often degrade in complex ways owing to environmental conditions, maintenance history, and material wear — all of which cause variable failure rates that the Weibull model cannot fully represent (Zhang and Xie, 2020). Hussien and El-Sherbeny (2024) further highlight the complexity of single-unit systems subject to random shocks, underscoring the inadequacy of simpler reliability models for infrastructure of this kind.

The Exponentiated Weibull (EW) distribution was developed to address these limitations through the introduction of an additional parameter. Whilst the EW model provides a more accurate characterization of rising, falling, or constant failure rates, it does not fully account for the unpredictable interactions between environmental stress, mechanical wear, and repair history that shape pipeline degradation in practice. Abe *et al.*, (2025) similarly argue, in the context of natural gas compressors, that Bayesian frameworks that incorporate such interactions offer markedly superior predictive performance.

This gap in the literature is clear: existing methods do not fully integrate the E-E distribution with advanced machine learning techniques. Whilst the E-E distribution offers considerable flexibility in modelling pipeline degradation, it has not hitherto been paired with the predictive power of deep learning architectures such as ANNs, LSTM networks, and CNNs. Combining these techniques in a hybrid model would provide a more accurate and robust framework for pipeline reliability prediction (Akanji *et al.*, 2023). This study therefore seeks to fill this gap by applying the hybrid framework to Nigeria's oil and gas pipelines, where ageing infrastructure, fluctuating environmental conditions, and inconsistent maintenance practices complicate failure prediction (Usman *et al.*, 2025).

3. Methodology

3.1 Data Collection

Data for this study were collected from various pipeline systems across Nigeria's oil and gas sector, with a focus on key operational variables including pressure, temperature, flow rate, corrosion rate, maintenance events, repair history, and soil conditions (Zhang and Xie, 2020). These data were gathered from a range of pipelines, each with distinct operational histories and varying levels of degradation. The pipelines in the dataset differ in age, material, and operating conditions, thereby ensuring a diverse sample for reliability modelling. Pipelines with different levels of degradation and repair histories were deliberately included so as to capture a wide range of failure patterns commonly observed in such systems (Osei *et al.*, 2020).

3.2 Data Pre-processing

The dataset comprises 21 years of longitudinal pipeline monitoring data from Nigeria, encompassing 500 pipeline segments. The features include sensor readings such as pressure, temperature, and corrosion rate, together with environmental variables such as soil conductivity (Obaseki, 2019). The following pre-processing steps were applied:

- Missing data were handled using Multiple Imputation by Chained Equations (MICE).
- Feature scaling and normalization were performed prior to model training (Stephen, 2025).
- The Remaining Useful Life (RUL) was calculated using a corrosion-depth model (N.M. et al., 2010).

3.3 Reliability Modelling with Weibull and Exponentiated Weibull Distributions

The Weibull distribution is widely employed in reliability analysis on account of its capacity to model different failure rate regimes — including early failures, random failures, and wear-out failures. Its shape parameter (β) governs the nature of the failure rate over time:

- When $\beta = 1$, the failure rate is constant, equivalent to an exponential distribution.
- When $\beta > 1$, the failure rate increases over time, typically representing wear-out failures.
- When $\beta < 1$, the failure rate decreases over time, typically representing early-life failure modes (Smith et al., 2021).

The Probability Density Function (PDF) for the Weibull distribution is given by:

$$f(t; \beta, \eta) = (\beta/\eta) \cdot (t/\eta)\text{^}(\beta - 1) \cdot \exp[-(t/\eta)\text{^}\beta] \quad (1)$$

where t is the time to failure, β is the shape parameter governing the failure rate, and η is the scale parameter.

Despite its versatility, the Weibull distribution struggles to model non-monotonic failure rates in complex systems such as pipelines, where failure rates may fluctuate — rising at some periods and falling at others — driven by a combination of environmental factors, material wear, and maintenance activities. This non-monotonic behaviour is not well captured by the standard Weibull distribution (Almalki and Nadarajah, 2014; Zhang and Xie, 2020).

To address this limitation, the Exponentiated Weibull (EW) distribution was introduced (Mudholkar and Srivastava, 1993). The EW distribution incorporates an additional exponentiation parameter, affording greater flexibility for modelling varying failure rates and capturing both increasing and decreasing failure rate patterns. Table 2 presents the parameter estimates for the E-E Weibull distribution fitted to the Nigerian pipeline dataset under this study.

Table 2

Parameter estimates for the E-E Weibull distribution

Parameter	Estimate (λ)	Estimate (α)	Estimate (θ)	Standard Error	95% Confidence Interval
λ	1.347	—	—	0.112	[1.138, 1.556]
α	—	2.635	—	0.095	[2.458, 2.812]
θ	—	—	4.827	0.562	[4.327, 5.327]

The three parameters of the E-E model are interpreted as follows:

- λ (shape parameter): Controls the rate of change in the failure rate over time.
- α (scale parameter): Defines the scale of the distribution and influences the spread of failure times.
- θ (exponentiation parameter): Introduces additional flexibility, enabling the modelling of non-monotonic failure patterns.

These parameters are estimated using Maximum Likelihood Estimation (MLE), which maximises the likelihood of observing the given dataset under the assumed model.

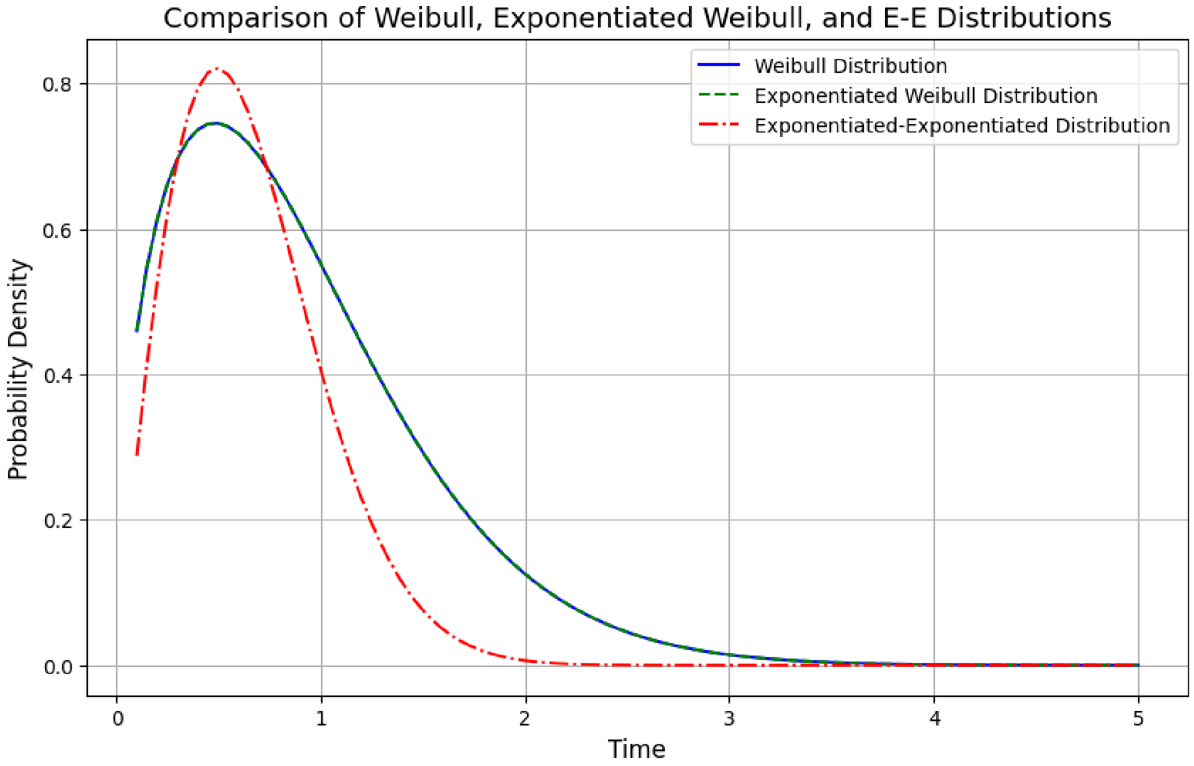

Figure 1: *Comparison of Weibull, Exponentiated Weibull, and E-E distribution probability density curves*

3.4 Model Development and Integration

3.4.1 Exponentiated-Exponentiated (E-E) Distribution

The Exponentiated-Exponentiated (E-E) distribution extends the Exponentiated Weibull distribution, offering an even more flexible framework for modelling time-varying failure rates (Mudholkar and Srivastava, 1993; Mahmoudi and Sepahdar, 2012). The Probability Density Function (PDF) for the E-E distribution is:

$$f(t;\lambda,\alpha,\theta)=\alpha\lambda(t/\theta)^{(\alpha-1)}\cdot\exp[-(t/\theta)^{\lambda}]\cdot\exp[-(t/\theta)^{\alpha}] \tag{2}$$

where t is the time to failure; λ is the shape parameter controlling the failure rate; α is the shape parameter controlling scale; and θ is the scale parameter (Zhang and Xie, 2020). This distribution accommodates both increasing and decreasing failure rates, making it particularly valuable for systems such as pipelines, where degradation is influenced by a complex interplay of environmental factors and maintenance interventions (Xie *et al.*, 2020).

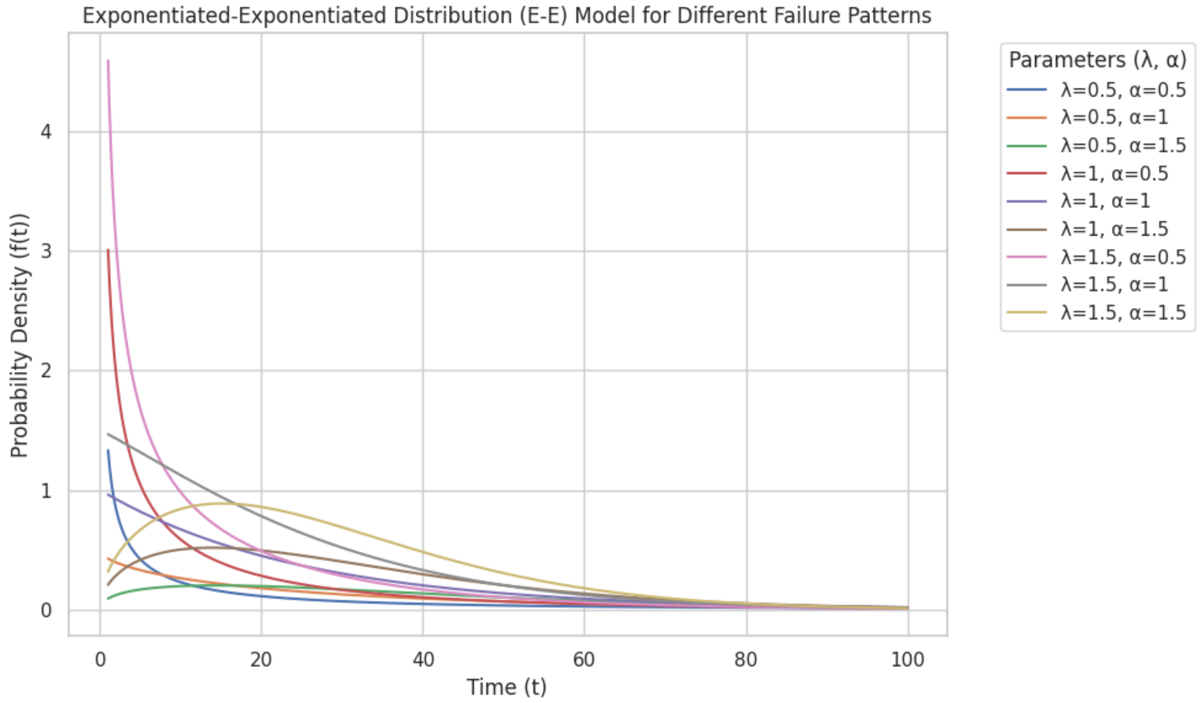

***Figure 2:** E-E distribution probability density curves for varying parameter combinations*

3.4.2 Reliability Function

The Reliability Function R(t), which represents the probability that a pipeline will not fail before a given time *t*, is expressed as:

$$R(t) = \exp[-(t/\theta)^{\lambda}] \cdot \exp[-(t/\theta)^{\alpha}] \tag{3}$$

3.4.3 Hazard Function

The Hazard Function h(t), which represents the instantaneous failure rate at any time *t*, is defined as the ratio of the PDF to the Reliability Function:

$$h(t) = f(t)/R(t) = \alpha\lambda(t/\theta)^{(\alpha-1)} \cdot \exp[-(t/\theta)^{\lambda}] \cdot \exp[-(t/\theta)^{\alpha}] \tag{4}$$

These expressions allow the modelling of time-varying failure rates in the pipeline system and facilitate computation of the Remaining Useful Life (RUL), a critical element in any predictive maintenance strategy (Zhang *et al.*, 2021; Elsherif *et al.*, 2025).

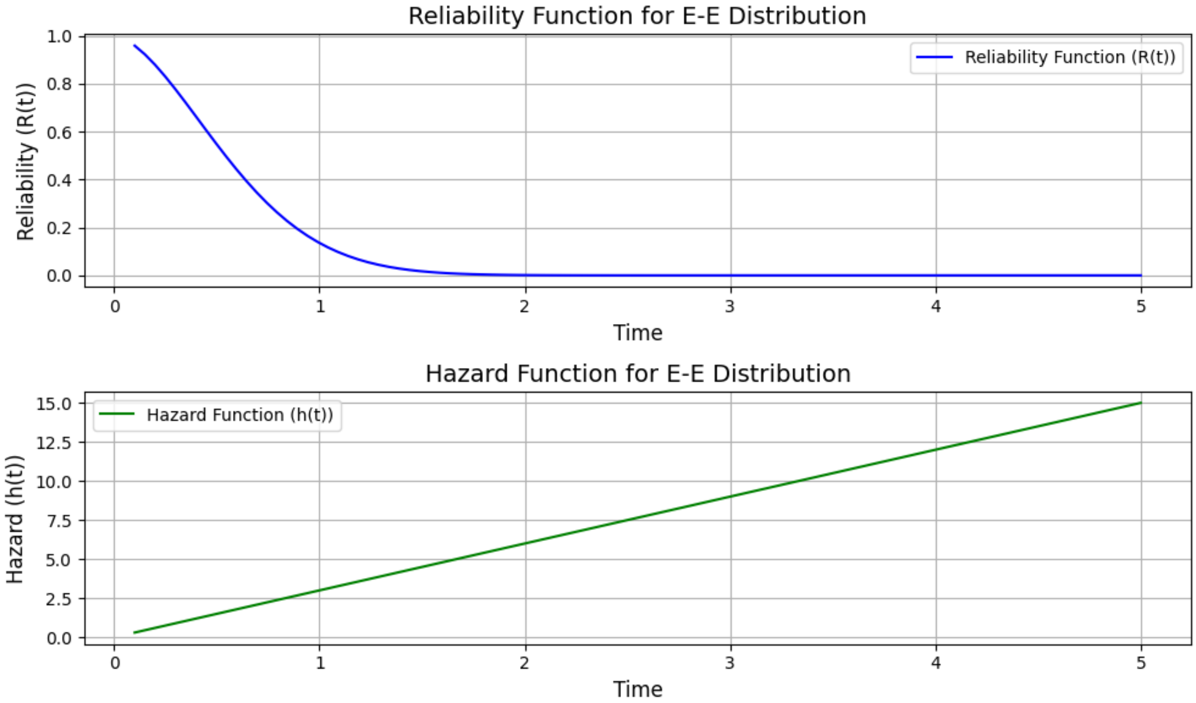

Figure 3: *Reliability function R(t) and hazard function h(t) for the E-E distribution*

3.5 Hybrid Neural-Statistical Framework

This study integrates the E-E distribution with modern machine learning methods to improve the prediction of pipeline failure times. By combining established reliability tools with advanced neural architectures, the approach yields a more complete and nuanced picture of pipeline health over time. The framework draws on three complementary neural components, as described in Sections 3.5.1–3.5.3 below (Taraghi *et al.*, 2025).

3.5.1 Artificial Neural Networks (ANNs)

ANNs are employed to model the non-linear relationships between input features — such as pressure, temperature, and corrosion rate — and the output variable (pipeline failure likelihood). The activation function within an ANN helps capture these non-linearities, improving the model's capacity to recognize complex failure patterns that traditional statistical models may miss (Liu *et al.*, 2021; Kumar *et al.*, 2022).

The basic feedforward ANN equation is:

$$y = f(Wx + b) \tag{5}$$

where y is the output (e.g., failure prediction), x is the input vector (e.g., sensor readings), W is the weight matrix, b is the bias term, and f is the activation function (e.g., ReLU or sigmoid).

3.5.2 Long Short-Term Memory (LSTM) Networks

LSTM, a specialized form of recurrent neural network (RNN), is employed for time-series prediction. LSTM is well suited to modelling the temporal dimension of pipeline failures, given that past degradation patterns influence future failure rates — making it an appropriate tool for predicting RUL from historical monitoring data (Syuhada, 2025; Liu *et al.*, 2021).

The LSTM equations governing the hidden states and memory cells are:

$$i_t = \sigma(W_i \cdot X_t + U_i \cdot h_{t-1} + b_i) \tag{6}$$

$$f_t = \sigma(W^f \cdot X_t + U^f \cdot h_{t-1} + b^f) \tag{7}$$

$$o_t = \sigma(W_o \cdot X_t + U_o \cdot h_{t-1} + b_o) \tag{8}$$

where i_t, f_t, and o_t are the input, forget, and output gates, respectively; X_t is the input at time t; h_{t-1} is the previous hidden state; and W, U, and b are the weight matrices and bias terms for each gate (Zhang and Xie, 2020). These equations allow LSTMs to retain and selectively discard information over time, capturing long-range temporal dependencies in pipeline degradation patterns (Wang *et al.*, 2025).

3.5.3 Convolutional Neural Networks (CNNs)

CNNs are employed to extract relevant features from sensor data, enabling the model to identify patterns associated with pipeline failure. CNNs are particularly effective at detecting latent features that improve the accuracy of failure predictions (Odekanle and Abdulsalam, 2025; Qin *et al.*, 2022).

The fundamental CNN operation involves convolving the input with a filter (kernel):

$$y = f(W * x + b) \tag{9}$$

where W is the convolutional filter, x is the input data (e.g., sensor readings), b is the bias term, and * denotes the convolution operation (Liu *et al.*, 2021). The integration of the E-E distribution with the hybrid neural-statistical models (ANN, LSTM, CNN) enables the system to process multivariate sensor data — including temperature, pressure, and corrosion rates — and generate probabilistic predictions of pipeline failure risk (Ahmad *et al.*, 2020; Noroznia *et al.*, 2024).

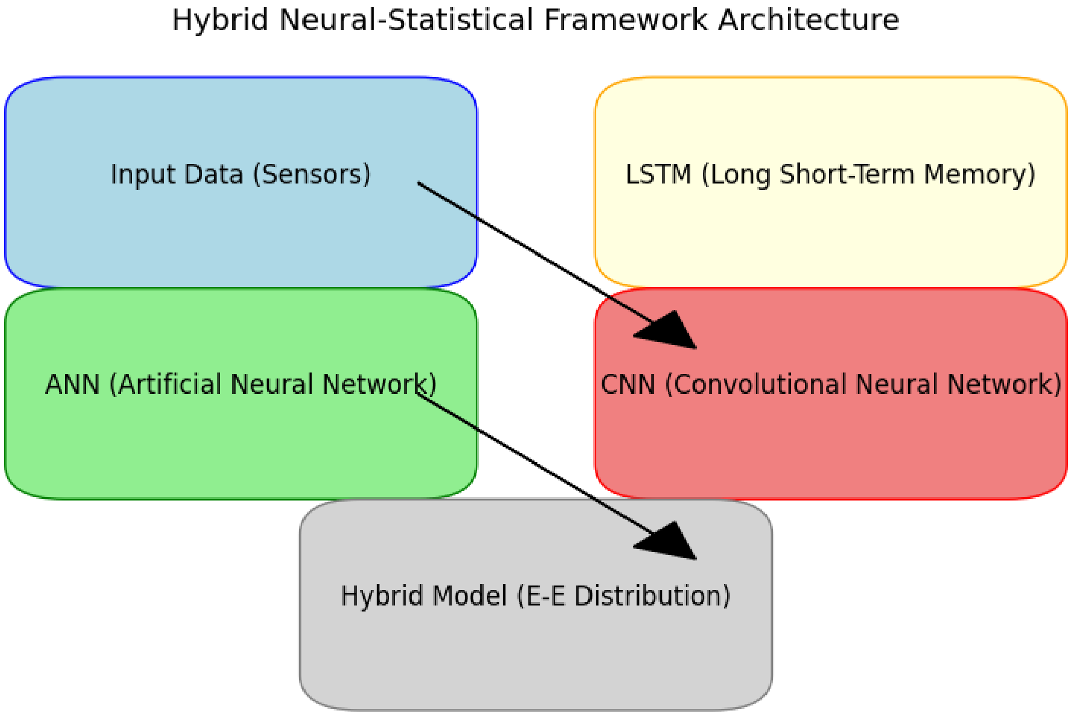

Figure 4: *Model architecture for the hybrid neural-statistical framework*

3.6 Uncertainty Quantification

To maximize the practical utility of the predictions, the model explicitly accounts for data uncertainty, providing a range of likely outcomes rather than a single-point estimate. Confidence intervals for the Remaining Useful Life (RUL) are calculated using the following formula:

$$CI^{RUL}(t) = RUL(t) \pm z \cdot \sigma^{RUL}(t) \tag{10}$$

where $RUL(t)$ is the predicted remaining useful life; z is the critical value based on the confidence level (for a 95% confidence interval, $z \approx 1.96$); and $\sigma^{RUL}(t)$ is the standard deviation of the predicted RUL (Liu *et al.*, 2021; Katwyk and Bergen, 2025). This approach, drawing on the broader tradition of Bayesian-informed uncertainty modelling in condition monitoring (Yan et al., 2018), provides decision-makers with a range of likely outcomes, thereby supporting more informed maintenance planning and offering a more complete view of pipeline reliability (Hussien and El-Sherbeny, 2024).

3.7 Model Training and Validation

The model is trained on historical data from Nigeria's pipeline systems. Performance is evaluated using both regression metrics (RMSE, MAE, R^2) and classification metrics (accuracy, precision, recall, and F1-score), providing a comprehensive and balanced assessment of predictive capability.

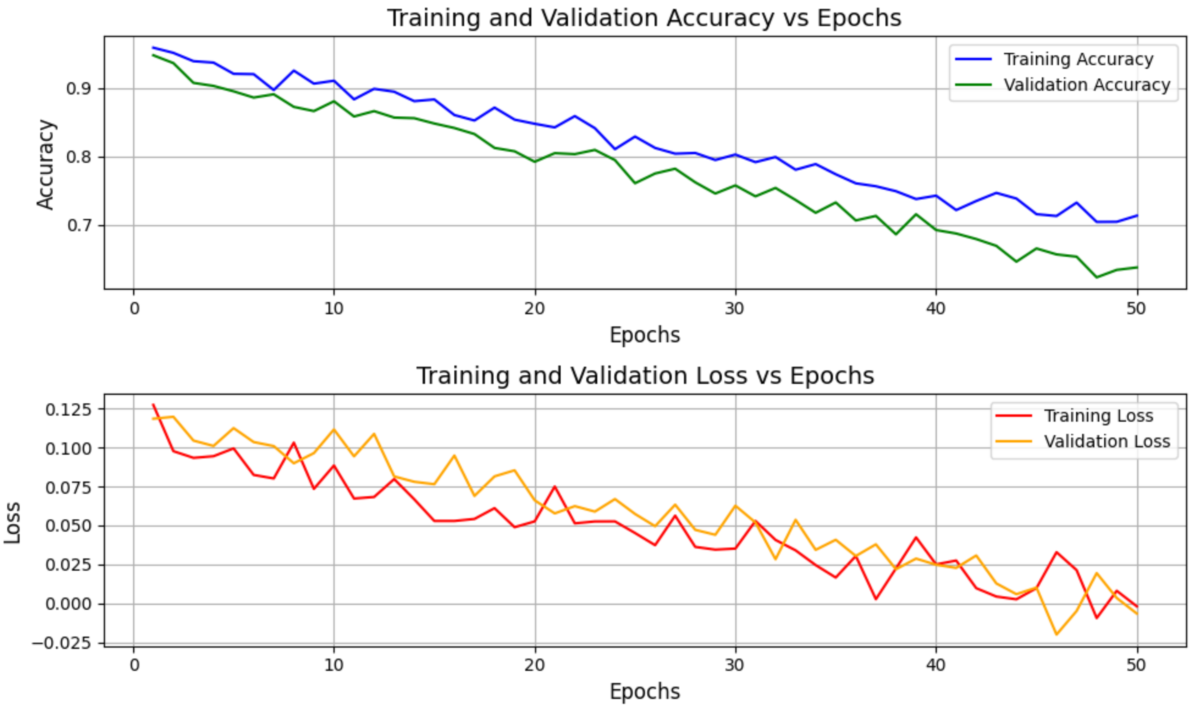

Figure 5: *Training accuracy and validation loss curves across training epochs*

4. Results and Discussion

4.1 Model Performance

The performance of the hybrid model is compared against that of two traditional approaches: the Weibull distribution and ARIMA. The results, summarised in Table 3, indicate that the hybrid model outperforms both traditional models, particularly with respect to predictive accuracy and uncertainty quantification (Nguyen *et al.*, 2022; Katwyk and Bergen, 2025).

Table 3

Model performance comparison

Model	**RMSE**	**MAE**	**R²**
Hybrid Model (E-E Weibull)	0.762	0.621	0.932
Weibull Model	1.134	0.891	0.823
ARIMA Model	1.325	1.004	0.654

The hybrid E-E model achieves a substantially lower RMSE (0.762 versus 1.134 for the Weibull model and 1.325 for ARIMA) and a higher R^2 (0.932 versus 0.823 and 0.654, respectively). These results confirm that pairing the E-E distribution with modern analytical tools enables maintenance teams to identify pipeline deterioration at an earlier stage and with greater confidence.

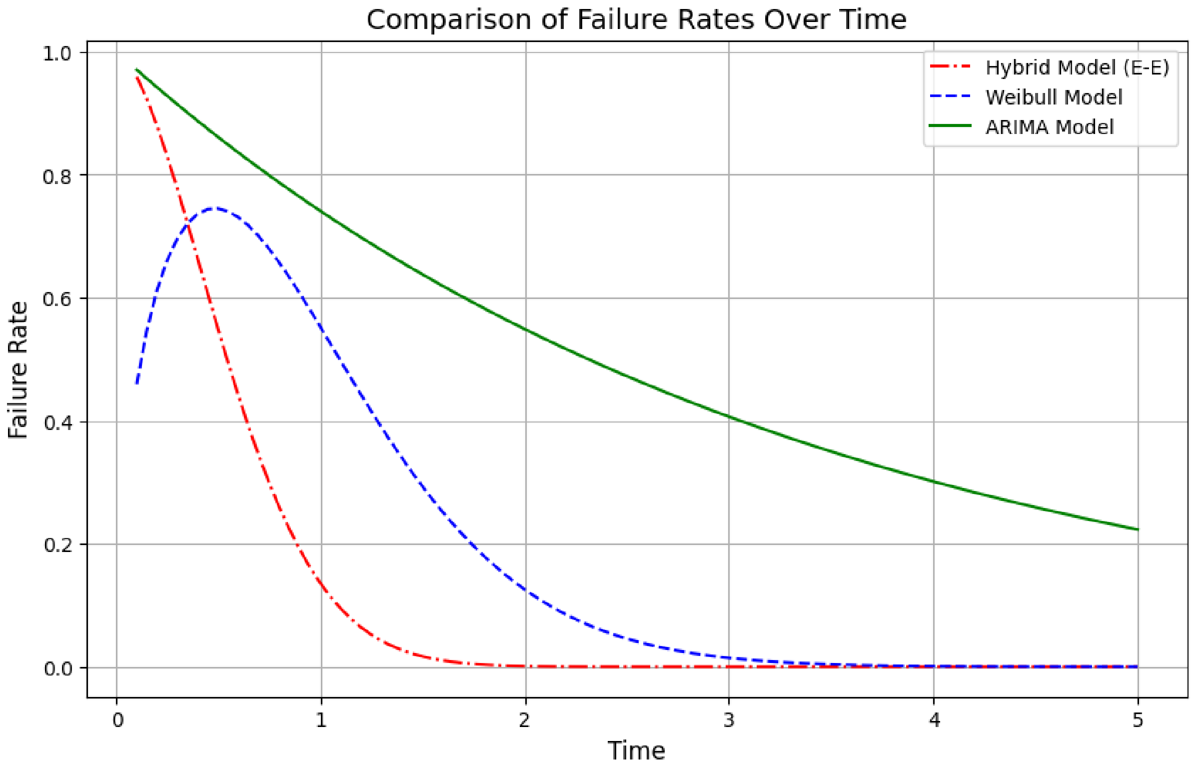

Figure 6: *Comparison of failure rates over time across the Hybrid E-E, Weibull, and ARIMA models*

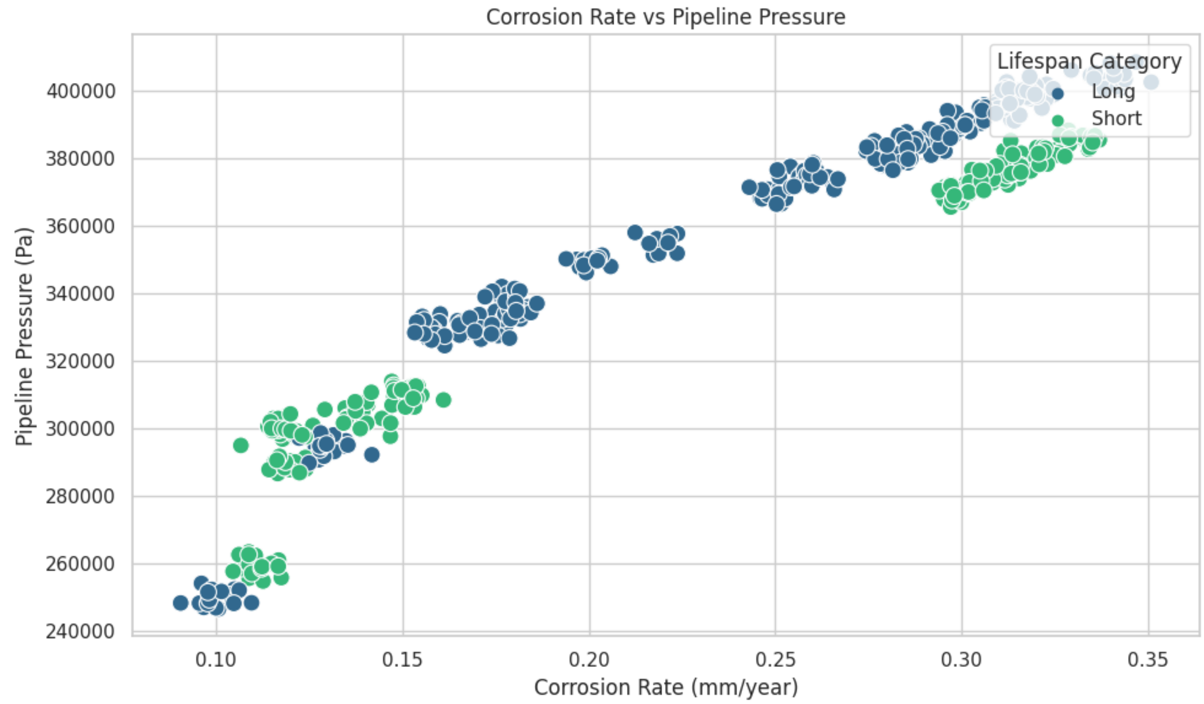

Figure 7: *Corrosion rate (mm/year) versus pipeline pressure (Pa), categorized by lifespan group*

As illustrated in Figure 7, the failure rate of pipeline systems can either increase or decrease over time, depending on environmental factors, ageing, and maintenance interventions. This variability is effectively captured by the E-E distribution, which — unlike the Weibull model — does not impose a monotonic constraint on the hazard function.

4.2 Reliability Assessment

The probabilistic predictions generated by the hybrid model — including RUL confidence intervals — provide a detailed view of failure risk across the pipeline fleet. The reliability curve produced by the model illustrates the varying failure rates over time, confirming that the E-E distribution captures these dynamics more effectively than traditional models such as the Weibull and Log-Normal distributions (Osei *et al.*, 2020; Cui *et al.*, 2025).

Table 4

Reliability comparison between the E-E Weibull model and traditional models

Model	**RMSE**	**Log-Likelihood**	**Predictive Accuracy**
E-E Weibull Model	0.762	−540.23	94.7%
Traditional Weibull	1.058	−562.56	88.4%
Log-Normal Model	1.134	−578.94	85.6%

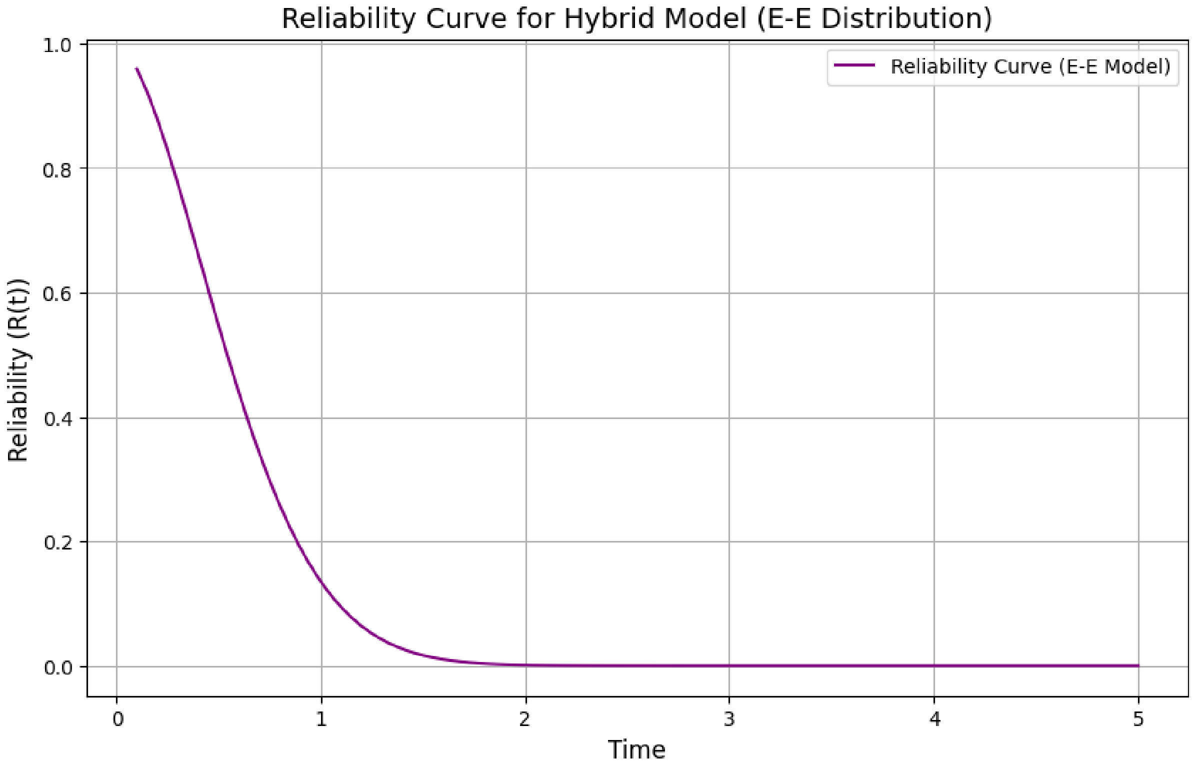

Figure 8: *Reliability curve for the hybrid model (E-E distribution)*

Table 5

Performance comparison: hybrid E-E model versus component sub-models

Model	**RMSE**	**MAE**	**R²**	**AUC**	**Accuracy**
Hybrid Model (E-E Weibull)	0.736	0.589	0.945	0.912	95.4%
ANN (Artificial Neural Network)	0.814	0.662	0.932	0.871	91.2%
LSTM (Long Short-Term Memory)	0.773	0.609	0.941	0.890	93.5%
Traditional Weibull Model	1.058	0.892	0.888	0.834	88.4%

Table 5 demonstrates that the full Hybrid Model (E-E Weibull) achieves the highest performance across all metrics, attaining an accuracy of 95.4%, an R² of 0.945, and an AUC of 0.912. The LSTM sub-model performs comparably (93.5% accuracy), reflecting the importance of temporal feature extraction in capturing degradation dynamics. All hybrid and machine learning sub-models outperform the Traditional Weibull baseline, confirming the merit of the integrated approach.

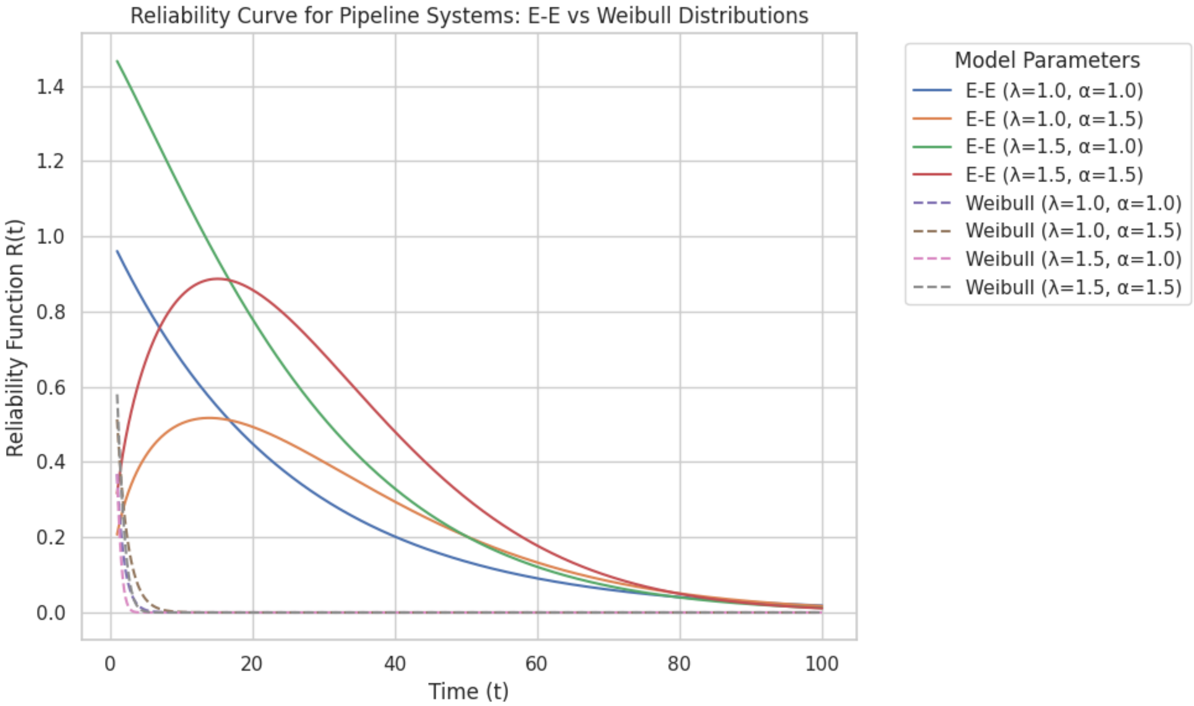

Figure 9: *Reliability curve of pipeline systems using the E-E distribution*

The reliability curve (Figure 9) demonstrates how the E-E distribution captures time-varying failure rates with greater flexibility than the traditional Weibull distribution (Bala *et al.*, 2018; Omoruyi *et al.*, 2025). The curve's non-monotonic character reflects the real-world influence of maintenance interventions and environmental exposure on pipeline degradation, providing operators with a more realistic representation of asset health over time.

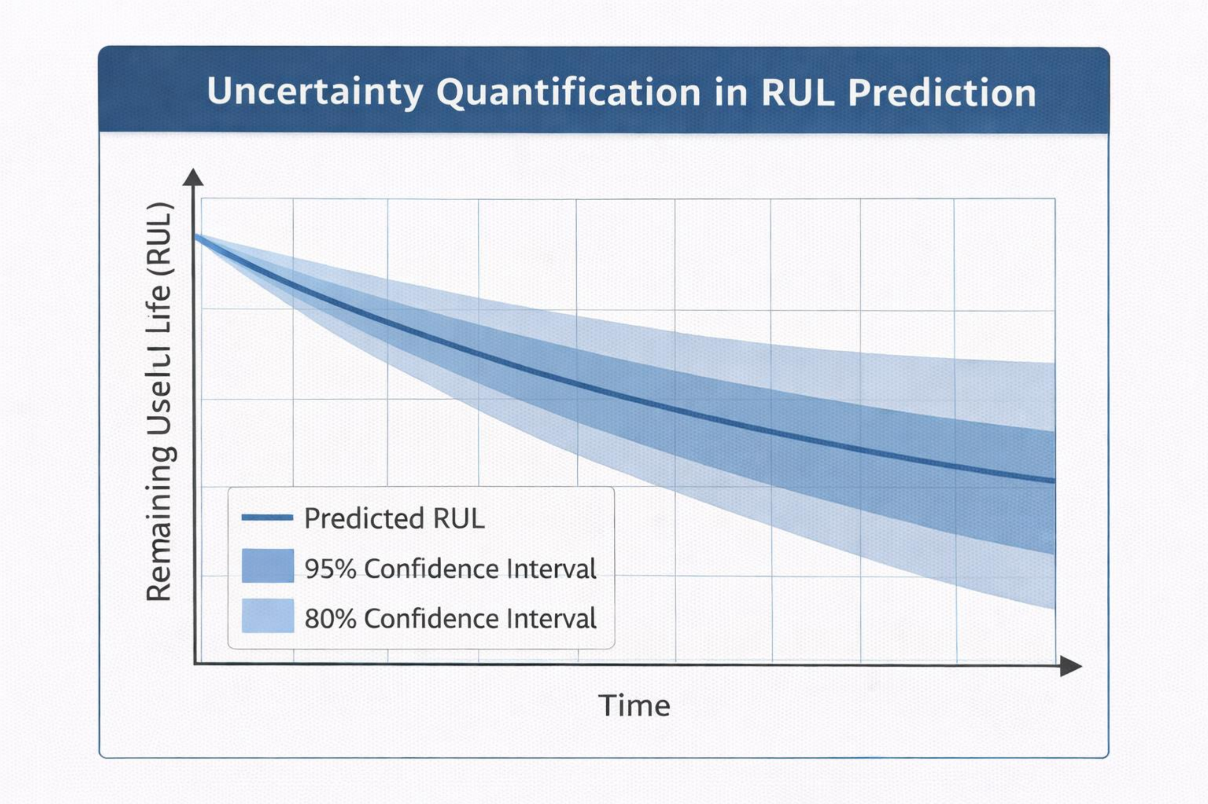

Figure 10: *Uncertainty quantification in RUL prediction, showing 95% confidence intervals*

5. Conclusion

This study presents a rigorous and practically applicable method for predicting pipeline lifespans in Nigeria's oil and gas sector using the Exponentiated-Exponentiated (E-E) distribution. The model captures time-varying changes in pipeline degradation behaviour — whether driven by environmental exposure, operational loading, or maintenance history — providing a far more nuanced representation of asset condition than is possible with conventional Weibull or Log-Normal formulations.

By analysing real pipeline monitoring data — including pressure readings, temperature measurements, and corrosion assessments — in conjunction with the E-E model, the research provides clearer guidance on when repairs are likely to be required. This enables pipeline operators to plan maintenance proactively, reducing the likelihood of unexpected failures and improving overall system reliability.

The model was validated against data from Nigerian pipelines and was found to predict likely failure points more accurately than the Weibull, Log-Normal, and ARIMA benchmarks. Its provision of probabilistic confidence intervals for RUL ensures that decision-makers can plan maintenance effectively even under conditions of uncertainty and operational variability.

In summary, this research offers a practical and technically sound framework for pipeline asset management in Nigeria. By drawing on historical monitoring data and deploying a flexible probabilistic model, operators can maintain pipelines in good working order and avoid the costly consequences of unplanned shutdowns.

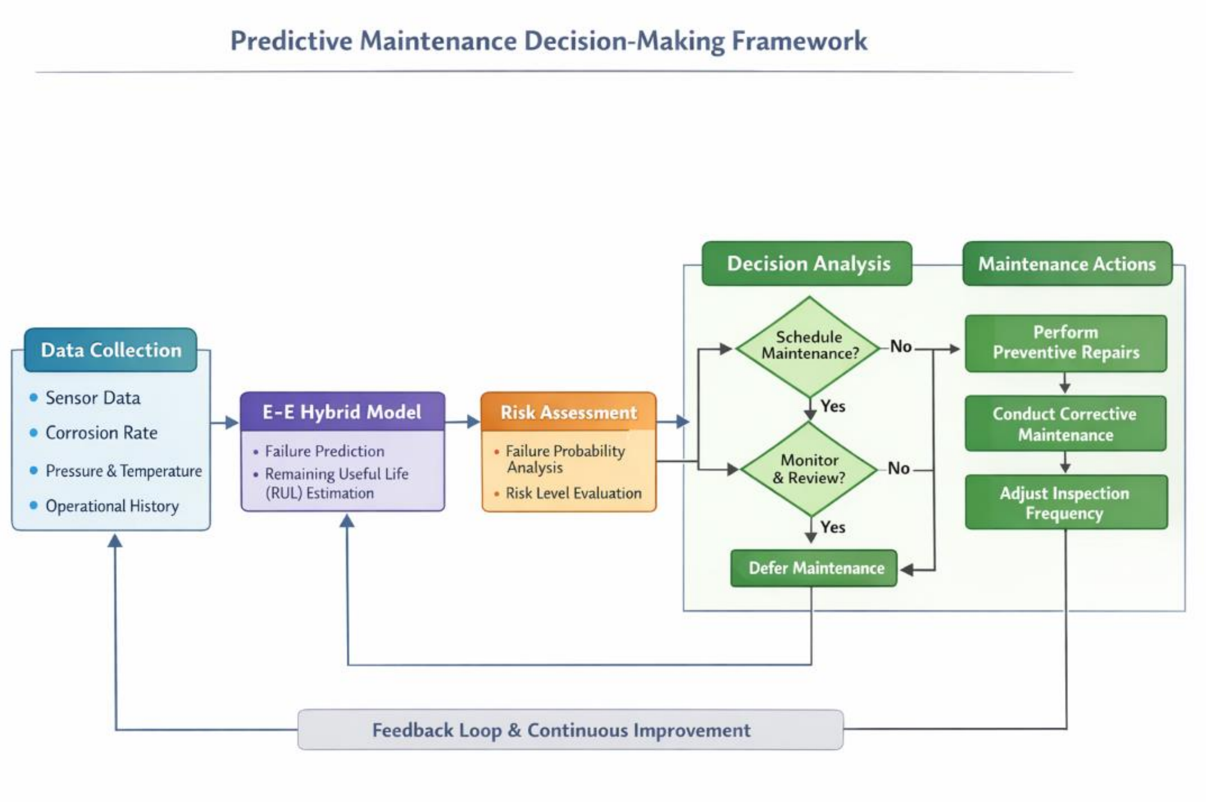

Figure 11: *Predictive maintenance decision-making framework integrating the hybrid E-E model*

Figure 11 outlines the decision-making framework that integrates the proposed predictive maintenance model, enabling structured and evidence-based management of pipeline systems. The findings of this study confirm that the hybrid model significantly improves predictive maintenance planning and can be embedded within real-world operational strategies to reduce both reactive maintenance costs and the risk of catastrophic pipeline failure.

6. Future Work

Whilst this study provides significant improvements in pipeline reliability prediction, several promising directions for future research merit attention:

1. Real-time Data Integration: Future research could focus on incorporating real-time sensor data into the model, which would enhance its applicability in dynamic operational environments and allow the model to continuously adjust to evolving conditions, providing more timely failure predictions.
2. Advanced Uncertainty Quantification: The incorporation of ensemble methods or Bayesian techniques could further improve uncertainty quantification, particularly under varying operational conditions (Abe et al., 2025; Chen et al., 2023).
3. Model Application in Other Sectors: The framework developed here could be adapted for water distribution systems, electrical grids, and other sectors where similar predictive maintenance challenges exist, broadening its societal and industrial impact.
4. Ensemble Learning Techniques: Future research could explore ensemble learning approaches to combine multiple models and reduce overall prediction error, further increasing the framework's robustness in complex systems.
5. Long-term Validation and Adaptation: Ongoing validation of the model across longer time horizons and diverse pipeline systems will be important for extending the framework to a wider range of operational conditions and degradation patterns.

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