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Artificial Neural Network Approach to Corrosion Risk Assessment of Buried Water Pipelines Using Pipe Condition Index

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ABSTRACT

The accurate prediction of corrosion risk in buried water pipelines is critical for ensuring the structural integrity and longevity of the water pipeline infrastructure. This study presents a data-driven approach using Artificial Neural Networks (ANN) to model corrosion susceptibility based on key pipeline and soil parameters. A set of input variables including pipe length, thickness, burial depth, age, diameter, operating pressure, as well as soil pH, salinity, resistivity, and electrical conductivity was evaluated using Multi-Criteria Decision Analysis (MCDA). The parameters were normalized, correlated with pipe condition index (PCI), and weighted using Analytic Hierarchy Process (AHP) to generate training and testing datasets. The ANN model was trained with Levenberg–Marquardt backpropagation and optimized with different hidden neuron configurations ranging from 3 to 10. Results showed that model accuracy improved with increasing neurons, with optimal performance achieved at 7–10 neurons, yielding an R^2 of 0.88 and RMSE of 0.10. The findings reveals ANN's capability in capturing complex nonlinear relationships inherent in corrosion processes and its suitability as a predictive tool for water pipeline asset management. This framework supports proactive maintenance, prioritization of high-risk segments, and integration into GIS-based decision support systems for sustainable infrastructure management.

Keywords: Corrosion Risk Prediction, Artificial Neural Network, Buried Pipelines, Pipe Condition Index, Multi-Criteria Decision Analysis

1.0. Introduction

Buried pipelines constitute one of the most critical components of modern infrastructure, enabling the safe and efficient transport of water, oil, gas, and other essential resources. Despite protective measures such as external coatings and cathodic protection, pipelines remain highly susceptible to corrosion due to prolonged interaction with soil environments and operational stresses (Roberge, 2008; Revie, 2008; Uhlig, 2011). Corrosion is a time-dependent degradation process influenced by multiple factors including pipe age, wall thickness, burial depth, internal operating pressure, and external soil parameters such as pH, electrical conductivity, resistivity, and salinity (Nyborg, 2002; Roberge, 2012). If left unmanaged, corrosion can result in pipe bursts, service disruptions, contamination of resources, environmental hazards, and severe economic losses (El Abbasy et al, 2014; Obaseki et al, 2017). The magnitude of these risks highlights the urgent need for reliable predictive frameworks to anticipate pipeline deterioration and guide proactive maintenance.
Traditional predictive approaches have often relied on mechanistic models and empirical correlations, such as the de Waard–Milliams model for CO_2 corrosion (Nyborg, 2002) or regression-based models using limited datasets (Revie, 2008). While these methods have provided useful insights, they generally underperform in real-world applications where nonlinear interactions dominate (Peng et al., 2020; Zewdu et al, 2020). For example, two pipelines with identical material and design specifications may experience markedly different corrosion rates depending on variations in local soil chemistry, microbial activity, or groundwater movement (Roberge, 2008; Moura and Santos, 2022). Such complexities underscore the limitations of linear and rule-based models in capturing the multifactorial nature of corrosion.

To overcome these limitations, data-driven machine learning techniques have increasingly been adopted for corrosion risk modelling (Xu et al., 2021; Macêdo et al., 2024). Among these, Artificial Neural Networks (ANNs) have gained prominence due to their ability to approximate nonlinear functions and uncover latent relationships in multi-dimensional datasets without requiring explicit assumptions about functional forms (Hornik et al, 1989; Raissi et al, 2019). ANNs have demonstrated superior performance in predicting corrosion rates, pit depth progression, and failure probabilities compared with regression or mechanistic models (El Abbasy et al., 2014; Peng et al., 2020; Obaseki et al., 2017). For instance, Ahmaid and Khoshnaw (2024) implemented a Levenberg–Marquardt ANN for underground gas pipelines and achieved a coefficient of determination (R^2) of 0.9999, while Obaseki et al. (2017) reported more than 99% predictive accuracy for Niger Delta oil and gas pipelines relative to conventional models. Similarly, Peng et al. (2020) and Xiao et al. (2023) employed radial basis function (RBF) neural networks to predict corrosion-induced failure probabilities with strong alignment to observed outcomes.

Recent advancements also integrate ANNs with optimization algorithms and statistical preprocessing techniques to further enhance accuracy. Xie, Ma, and Liu (2024) employed principal component analysis (PCA) with a hybrid SSA-ELM neural network to predict pitting corrosion depth, reducing mean absolute percentage error by 42.7%. Similarly, Xie et al. (2024) combined knowledge-graph features with a particle swarm-optimized backpropagation (PSO-BP) neural network, achieving R^2 values above 0.99. These studies affirm ANN's flexibility in incorporating diverse data types and its adaptability for complex corrosion modelling.

Despite these successes, implementing ANN effectively requires careful parameter selection, preprocessing, and architecture optimization. Selection of critical variables spanning pipeline geometry, operational characteristics, and soil environment ensures that the multifactorial drivers of corrosion are captured (Tavakoli et al., 2019; Kumari et al., 2022). Preprocessing techniques such as normalization reduce bias from different units of measurement, while variable weighting through Multi-Criteria Decision Analysis (MCDA) and Analytic Hierarchy Process (AHP) improves interpretability and input balance (Obaseki et al., 2017). Furthermore, determining the optimal number of hidden neurons is essential to balance model complexity and generalization (Ahmaid and Khoshnaw, 2024).

Building on these insights, this study focuses exclusively on the development of an ANN-based predictive framework for corrosion risk in buried pipelines. The specific objectives are to:

1. Identify and preprocess pipeline and soil parameters critical to corrosion risk.
2. Develop and train an ANN using Levenberg–Marquardt backpropagation for predictive modelling.
3. Optimize ANN architecture by testing hidden neuron configurations.
4. Validate the ANN's performance using statistical metrics including Root Mean Squared Error (RMSE) and coefficient of determination (R^2).

By centering on ANN modelling approach, this research contributes to the advancement of data-driven infrastructure management and provides a replicable tool for pipeline operators. The outcome is expected to support proactive maintenance, risk prioritization, and the integration of predictive analytics into pipeline integrity management systems, particularly in resource-constrained regions where conventional monitoring is limited.

2.0 Methodology

This study adopted a systematic approach to develop a predictive model for assessing corrosion risk in buried pipelines using Artificial Neural Networks (ANNs). The methodology was designed to ensure that critical pipeline and soil parameters were properly identified, pre-processed, and structured for ANN training and validation.

2.1. The Study Area

The study was carried out at Edo State Polytechnic, Usen, located in Ovia Southwest Local Government Area of Edo State, Nigeria. Usen lies within the humid tropical climatic zone, which is characterized by high annual rainfall and relatively high humidity that significantly influence soil aggressiveness and, consequently, pipeline corrosion. Geographically, the Polytechnic campus is bounded within the following coordinates (UTM Zone 31N): Northwest: 06°44′20″N, 05°02′40″E, Northeast: 06°44′20″N, 05°03′15″E; Southwest:

06°43′48″N, 05°02′40″E, Southeast: 06°43′48″N, 05°03′15″E. This quadrangular extent encloses the main campus and its buried pipeline infrastructure, forming the spatial framework for corrosion risk modeling in this study. The water distribution network at Edo State Polytechnic has a total length of approximately 4,008.6 meters, consisting of interconnected buried pipelines supplying water across the institution. Figure 1 show the map of the study area

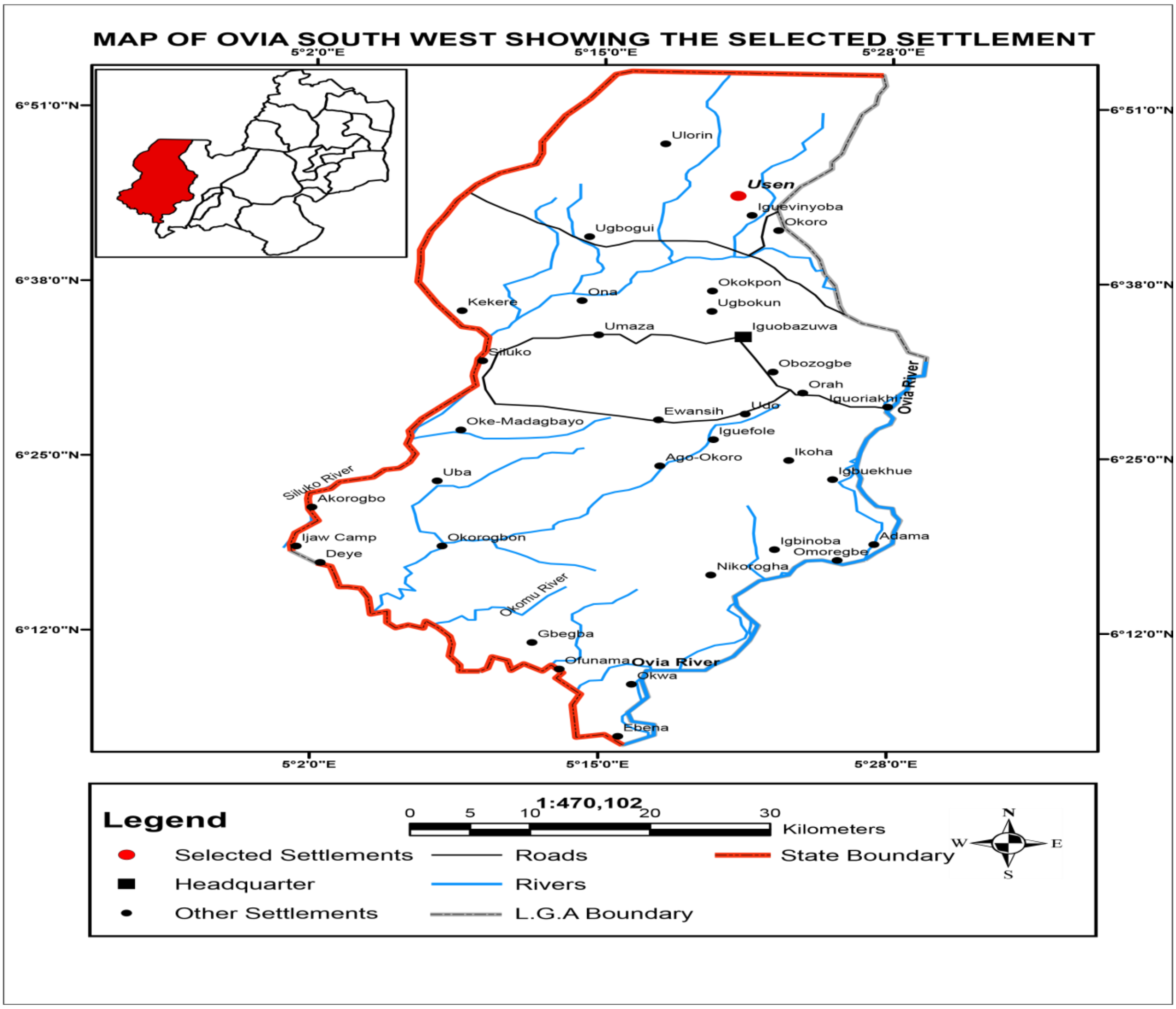

Figure 1: Map of the Study Area

The choice of this location was influenced by the lack of prior geospatial and predictive corrosion assessments of its pipeline network, despite recurring issues of pipe failure, poor maintenance records, and inadequate mapping of underground utilities. These characteristics make the site an ideal case study for developing and testing ANN-based corrosion prediction models.

2.2 Data Collection and Input Parameters

Two categories of parameters were considered: pipeline characteristics (pipe length, wall thickness, burial depth, age, diameter, and internal operating pressure) and soil environmental factors (pH, electrical conductivity, salinity, and resistivity). These variables were selected based on their established influence on corrosion processes (Roberge, 2008; Revie, 2008; Nyborg, 2002). Pipeline characteristics capture the intrinsic physical and operational conditions that affect degradation, while soil variables represent the electrochemical environment driving external corrosion.

Data were obtained from published literature, prior studies, and simulated datasets based on realistic engineering ranges. This ensured sufficient variability to enable the ANN to learn from different pipeline conditions. For example, pipe age ranged from 1 to 50 years, burial depth from 0.5 to 3.0 m, wall thickness from 5 to 50 mm, and soil resistivity from 10 to 5000 Ω·m. Such ranges align with values used in earlier corrosion prediction studies (Obaseki et al., 2017; ElAbbasy et al., 2014).

2.3 Data Preprocessing and Variable Weighting

Preprocessing was carried out to improve data quality and suitability for ANN modelling. Missing values were handled, and outliers were examined to minimize distortion. Since input variables had different measurement units such as: bar, mm, Ω·m. Min–max normalization was applied to rescale values between 0 and 1 to ensure that no single parameter dominated the learning process as shown in equation 1 (Moura and Santos, 2022).

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} = X_{\min}} \qquad (1)$$

where X is the raw value, Xmin and Xmax are the minimum and maximum observed values, and Xnorm is the normalized variable.

To prioritize variables according to their relative influence on corrosion, a Multi-Criteria Decision Analysis (MCDA) framework was adopted. The Analytic Hierarchy Process (AHP) was used to assign weights to each attribute, reflecting expert judgment and literature consensus on their importance (Obaseki et al., 2017; Kumari et al., 2022). Weighted scores were aggregated into a Pipe Condition Index (PCI), which served as the output target variable for the ANN. The normalized weights were derived as shown in equations 2 and 3:

$$w_i = \frac{\lambda_{\min} - n}{(n-1)} \qquad (2)$$

where w_i is the weight of the i^{th} parameter, λmax is the principal eigenvalue, and *n* is the number of variables.

$$PCI = \sum_{i=1}^{n} w_i \times X_i \qquad (3)$$

where X_i is the normalized score of the i^{th} attribute and w_i is its weight.

2.4 Artificial Neural Network Model Development

The ANN model was implemented as a feedforward multilayer perceptron (MLP) with supervised learning. The architecture consisted of:

i. An input layer representing the water pipeline and soil parameters,
ii. A single hidden layer with neurons varied systematically from 3 to 10, and
iii. An output layer predicting the Pipe Condition Index (PCI).

Figure 2 shows the diagrammatical representation of the architecture adopted in the reserch work.

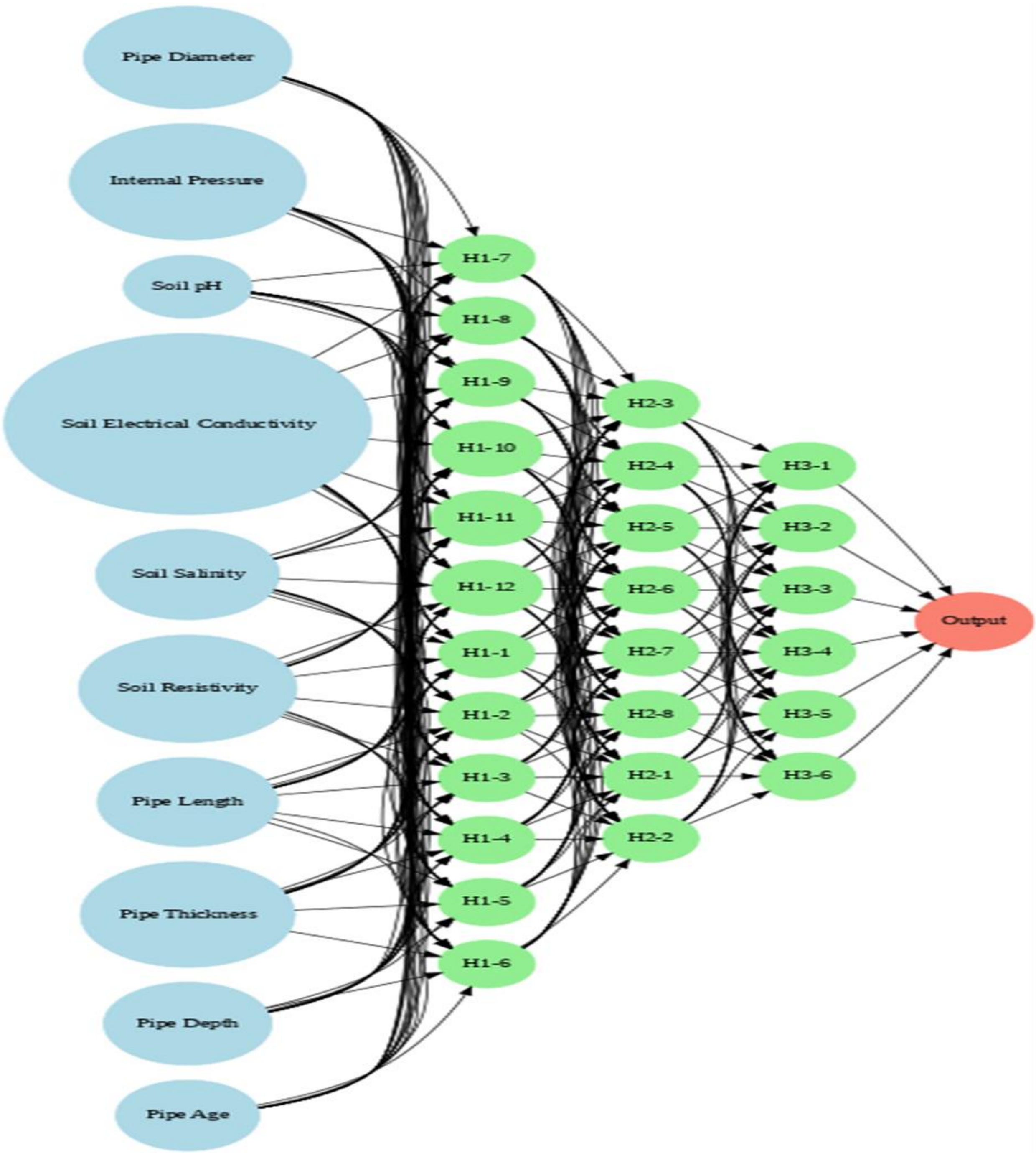

Figure 2: ANN Architecture for the work.

The network was trained using the Levenberg–Marquardt backpropagation algorithm, widely recognized for its efficiency and convergence speed in engineering applications (Ahmaid and Khoshnaw, 2024; Hornik et al., 1989). Equations 4 was employed for this purpose.

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{4}$$

where: *y* represents the output (predicted PCI), x_i are the input variables (pipeline and soil parameters), wi are the connection weights, *b* is the bias, *f* is the activation function.

The hidden layer transformation is given by equation 5 and the output layer by equation 6:

$$h_j = f\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right),\ j = 1, 2, 3..., m \tag{5}$$

$$\hat{y} = f_0\left(\sum_{j=1}^{m} v_j h_j + b_0\right) \tag{6}$$

where h_j is the hidden neuron output, v_j is the weight from hidden to output layer, and f_o is the output activation function.

Training was conducted using the Levenberg–Marquardt backpropagation algorithm, which minimizes the error function as shown in equation 7:

$$E = \frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2 \tag{7}$$

where y_k is the observed PCI, $\hat{y}_k$ is the predicted PCI, and N is the number of samples.

2.5 Training, Validation, and Cross-Validation

The dataset was divided into training (80%) and testing (20%) subsets to evaluate generalization performance. To minimize overfitting and improve robustness, five-fold cross-validation was employed. This ensured that the model's predictive accuracy was assessed across multiple random partitions of the dataset, enhancing reliability (Raissi et al., 2019; Xu, Wang, & Zhang, 2021).

2.6 Model Evaluation and Sensitivity Analysis

The ANN's performance was assessed using:

Root Mean Squared Error (RMSE), equation 8 and,

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(y_k - \hat{y}_k)^2} \tag{8}$$

Coefficient of Determination (R^2), equation 9.

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(y_k - \hat{y}_k)^2}{\sum_{k=1}^{N}(y_k - \hat{y}_k)^2} \tag{9}$$

These metrics were selected due to their widespread use in predictive modelling of corrosion and infrastructure risk (Peng, Yang, & Fang, 2020; Xiao, Yu, & Zhang, 2023).

Finally, sensitivity analysis was conducted using equation 10 to determine the relative contribution of each input variable to corrosion risk prediction. This step enhanced the interpretability of the ANN model, aligning its predictions with established engineering knowledge of corrosion mechanisms (ElAbbasy et al., 2014; Zewdu, 2020).

$$I_i = \frac{\sum_{j=1}^{m} \left| w_{ij} \times v_j \right|}{\sum_{j=1}^{n} \sum_{j=1}^{m} \left| w_{ij} \times v_j \right|} \tag{10}$$

where I_i is the relative importance of input variable i, w_{ij} are the input-to-hidden weights, and v_j are the hidden-to-output weights.

3.0 Results and Discussion

The predictive modelling of corrosion risk in buried pipelines was carried out using Artificial Neural Networks (ANN) trained on both pipeline and soil parameters. The results presented here highlight the input data structure, the optimized ANN configurations, and the model's predictive accuracy.

3.1 Input Parameters for ANN

The study employed Multi-Criteria Decision Analysis (MCDA) to structure the input dataset into two domains: pipeline-specific characteristics and soil environmental properties (Table 1).

Table 1: MCDA Input Parameters

Parameter	Category	Unit	Range (Min–Max)
Pipe Length	Pipe	km	0 – 10
Pipe Thickness	Pipe	mm	5 – 50
Pipe Depth (Burial)	Pipe	m	0.5 – 3
Pipe Age	Pipe	years	1 – 50
Pipe Diameter	Pipe	mm	100 – 800
Internal Pressure (Operating)	Pipe	bar	0 – 100
Soil pH	Soil	pH units	4 – 8
Soil Electrical Conductivity	Soil	µS/cm	50 – 200
Soil Salinity	Soil	ppt	0 – 35
Soil Resistivity	Soil	Ω·m	10 – 5000

These variables were normalized and weighted using the Analytic Hierarchy Process (AHP) to generate the Pipe Condition Index (PCI), which served as the target output for the ANN.

3.2 Correlation and Attribute Weighting

Correlation analysis revealed strong relationships between corrosion risk and parameters such as pipe age, wall thickness, burial depth, soil resistivity, and soil pH. For example, lower soil resistivity was inversely correlated with PCI, confirming its role as a key driver of electrochemical corrosion. The AHP weighting scheme assigned higher importance to pipe age (w = 0.22) and soil resistivity (w = 0.19) compared with parameters such as pipe length (w = 0.06). These weights provided a balanced multi-factorial representation of corrosion drivers for ANN training.

3.3 ANN Model Optimization

The ANN was implemented as a feedforward multilayer perceptron (MLP) trained with Levenberg–Marquardt backpropagation. The hidden layer neurons were varied from 3 to 10 to identify the optimal configuration (Table 3).

Table 3: ANN Performance Metrics by Hidden Neurons

ANN Model	Hidden Neurons	MSE	R^2
ANN (3 neurons)	3	0.0015	0.80
ANN (4 neurons)	4	0.0012	0.82
ANN (5 neurons)	5	0.0011	0.83
ANN (6 neurons)	6	0.0010	0.85
ANN (7 neurons)	7	0.0009	0.87
ANN (10 neurons)	10	0.0008	0.88

The results show consistent improvement in predictive accuracy as the number of neurons increased. The best performance was observed at 7–10 hidden neurons, achieving an R^2 of 0.88 and a mean squared error (MSE) of 0.0008.

3.4 Model Accuracy and Generalization

The ANN achieved a Root Mean Squared Error (RMSE) of 0.10 and $R^2 = 0.88$ on the test dataset, indicating strong predictive power and generalization ability. Cross-validation confirmed the robustness of the model, with minimal variance in performance across folds.

4.0 Conclusion

This study developed an Artificial Neural Network (ANN) model for predicting corrosion risk in buried pipelines using pipeline and soil parameters structured through Multi-Criteria Decision Analysis (MCDA) and weighted by the Analytic Hierarchy Process (AHP). The Pipe Condition Index (PCI) was adopted as the target variable, enabling the model to capture the nonlinear interplay between pipe attributes and soil environmental conditions.

The research confirms the suitability of ANN as a predictive tool for pipeline integrity assessment. By integrating diverse variables and learning from their complex interactions, the ANN provides an effective framework for proactive maintenance and risk-based asset management. The approach demonstrates that artificial intelligence can complement conventional monitoring techniques, offering operators a more data-driven and preventive approach to corrosion management.

The study contributes to knowledge by establishing a replicable ANN-based modelling framework that can be adapted to similar pipeline networks. Beyond its current application, the framework can be extended through integration with Geographic Information Systems (GIS) for spatial decision support and with real-time sensor networks for continuous risk monitoring.

In light of these findings, it is recommended that pipeline operators and utility managers adopt ANN-based predictive tools as part of their maintenance strategies. Integrating such models into digital asset management systems can enhance early detection of high-risk segments, reduce maintenance costs, and minimize service disruptions. Researchers should further expand the dataset through field-based measurements, explore transfer learning across different pipeline networks, and apply explainable AI approaches to improve interpretability and industry acceptance. These steps will strengthen the role of ANN in supporting safe, reliable, and sustainable pipeline infrastructure management.

References

Ahmaid, A. and Khoshnaw, F. (2024). Corrosion rate prediction for underground gas pipelines using a Levenberg–Marquardt artificial neural network (ANN). *Advances in Materials Science*, 24(4), 150–168.

Cai, J., and Cottis, R. A. (1999). Phenomenological modelling of atmospheric corrosion using an artificial neural network. *Corrosion Science*, 41(10), 1807–1823.

ElAbbasy, M. S., Senouci, A., Zayed, T., and Parvizsedghy, L. (2014). Artificial neural network models for predicting condition of offshore oil and gas pipelines. *Automation in Construction*, 44, 236–245.

Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, 2(5), 359–366.

Kumari, P., Halim, S. Z. and Kwon, J. S. I. (2022). An integrated risk prediction model for corrosion-induced pipeline incidents using ANN and Bayesian analysis. *Process Safety and Environmental Protection*, 167, 34–44.

Macêdo, B. da S., Boratto, T., Saporetti, C., and Goliatt, L. (2024). A review of deformations prediction for oil and gas pipelines using machine and deep learning. In *Deformation Science in Pipelines*.

Moura, H., and Santos, H. (2022). Reviewing machine learning of corrosion prediction in a data-oriented context. *npj Materials Degradation*, 6(1).

Nyborg, R. (2002). Overview of CO_2 corrosion models for wells and pipelines. *Paper Presented at NACE International Conference.*

Obaseki, M., Nwankwojike, B. N., and Abam, F. (2017). Artificial Neural Network simulation model for predicting oil and gas pipeline corrosion rate in Nigeria Niger Delta. *Energy Materials Journal.*

Peng, Y., Yang, F., and Fang, Z. (2020). RBF neural network modelling for pipeline failure probability. *Frontiers in Earth Science*, 11, 1148407.

Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686–707.

Revie, R. W. (2008). *Corrosion and corrosion control: An introduction to corrosion science and engineering* (4th ed.). John Wiley & Sons.

Roberge, P. R. (2008). *Corrosion engineering: Principles and practice*. McGraw-Hill.

Roberge, P. R. (2012). *Handbook of corrosion engineering*. McGraw-Hill.

Tavakoli, R., Najafi, M., and Sharifara, A. (2019). Artificial neural networks and adaptive neurofuzzy models for prediction of remaining useful life. *arXiv. 1909.02115*.

Uhlig, H. H. (2011). *Corrosion and corrosion control*. Wiley.

Xiao, R., Yu, T. and Zhang, L. (2023). Prediction of corrosion failure probability of buried oil and gas pipelines using RBF neural network. *Frontiers in Earth Science*, 11, 1148407.

Xie, H., Ma, P., & Liu, D. (2024). Prediction model for pipeline pitting corrosion based on SSARELM and PCA. *Materials Corrosion Journal*, 80(11), 1118–1128.

Xie, R., Fan, Z., Hao, X., Luo, W., Li, Y., Zhao, Y. and Han, J. (2024). Prediction model of corrosion rate for oil and gas pipelines based on knowledge graph and neural network. *Processes*, 12(11), 2367.

Xu, J., Wang, S. and Zhang, H. (2021). Uncertainty-aware Bayesian neural network for pipeline corrosion risk. *Journal of Corrosion Science.*

Zewdu T.W. (2020). Data-driven method for enhanced corrosion assessment of reinforced concrete structures. *arXiv. Submitted July 1, 2020.*

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