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Hybrid Neural Network Approaches to Produced Water Quality Forecasting and Management in Nigerian Oil Fields

Howard, C. C.[1], Howard, I, C.[2,*]
[1]Department of Mathematics/Computer Science, Faculty of Science, University of Africa
Toru-orua, Sagbama. Bayelsa State, Nigeria
[2]Department of Chemistry/Biochemistry, Federal Polytechnic, Nekede Owerri. Imo State, Nigeria
*Corresponding author: dromiete_ib@yahoo.com

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ABSTRACT: The management of produced water is a significant challenge for environmental agencies and operating companies in Nigerian oil environments, where escalating water-cut ratios persist. This research proposes and compares different artificial neural network (ANN) models with the integration strategies of Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Wavelet Transform (WT) for forecasting the quality variables TDS, Oil & Grease, Chloride, and Heavy Metals. Data for six prominent oil fields in the Niger Delta for 2015-2023 have been employed for analyses with all three models: ANN-PSO, ANN-GA, and ANN-WT. These models have confirmed that ANN-PSO models predict with higher precision compared to all other models, with regression values above 0.94 for forecasting TDS. The values for Root Mean Square Error (RMSE) have been found to vary between 23% and 31% lower than ANNs. The model ANNE-WT has outperformed with a regression value of 0.92 for forecasting chloride levels with a mean absolute percentage error (MAPE) value of 4.7% for Seasonal components.
These models offer oil field operators an adequate predictive system that can proactively optimize water treatment systems and facilitate regulatory compliance. These results help address the issue of water cut increase in a more sustainable manner within the mature oil field settings.

Keywords: produced water, artificial neural networks, hybrid models, water quality forecasting, Nigerian oil fields, Niger Delta.

1. Introduction

Produced water (PW) is considered to be the largest amount of waste created during petroleum and gas production, sometimes it is even several times higher than the volume of petroleum extracted in mature deposits (Howard 2016). Worldwide, over 250 million barrels of produced water are created every day. These have complex environmental and processing issues (Jiménez *et al*., 2021). The situation is even worse in Nigeria's Niger Delta, with mature petroleum deposits that have boosted water/oil ratios—initially below 3:1 but above 15:1 in old accumulations (Adewumi et al., 2023). Produced waters have complex and variable components. They mainly include dissolved salts, petroleum residues, heavy metals, and chemical inhibitors, which leads to corrosive scaling and contamination release (Howard *et al*., 2011, Howard, 2016, Howard, 2022, Nwankwo & Amadi, 2023).

Reliable forecasting of produced water quality plays a critical role in maximizing treatment process performance, optimizing reinjection plans, and dealing with environmental regulations concerning discharge (Howard 2019). Conventional empirical and statistical approaches such as multiple linear regression models and trending analyses have struggled to represent non-linear correlations between several physicochemical variables (Howard 2019, Ahmadi & Chen, 2020). Artificial neural networks (ANNs), which are non-linear models for simulating complex data without prior assumptions about mathematical representations, have been increasingly popular for reproducing non-linear correlations between several variables for forecasting produce water quality. Nevertheless, these models are susceptible to the problem of overfitting, the risk of convergence to a local minimum, and deteriorating levels of generalization within noisy environment data (Srivastava *et al.*, 2021).

Nevertheless, to counter these weaknesses, there has been the integration of hybrid approaches that include ANNs and other techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Wavelet Transform (WT) to optimize these processes. These approaches are seen to improve the accuracy and explanatory capability for most environmental applications (Kumar & Singh, 2022; Rajaee *et al.,* 2019). Despite these developments, relatively little work has been done on using these combined ANN models for forecasting the quality trends of produced water, especially in the Nigerian petroleum regions. Presently, current local research practices have been focused on regression models and traditional deterministic models. These might not effectively model complex dependencies between operating and geochemical parameter interactions (Ezeuko *et al.,* 2021, Howard, *et al.,* 2022).

Therefore, this research work designs and compares the performance of three types of hybrid ANN models: ANN-PSO, ANN-GA, and ANN-WT, for forecasting critical produced-water quality parameters such as TDS, chlorides, oil and grease, and heavy metals. This work will rely on past data covering a period of nine years (2015-2023) for six prominent Niger Delta oil fields. The overall aim is to: (1) design and test these hybrid models for forecasting purposes, (2) test their performance using extensive long-term datasets, (3) conduct sensitivity analyses to determine which variables play a leading role, (4) investigate their efficiency for real-time computations, and (5) propose tested models for sustainable management practices for produced waters.

2. Literature Review

Modeling for produced-water forecasting has developed in line with advances in data-oriented and computational models. Initial attempts mainly emphasized descriptive statistics and regression model approaches for isolating individual parameters, which did not prove transferable for various operating environments. Singh *et al.,* (2009), for example, used feedforward networks for forecasting water quality with relatively good results (R^2 = 0.73-0.81), but these models did not possess adequate structures for addressing time-related changes. These challenges were addressed with the development by Palani *et al.,* (2008) that integrated time series models to the ANN architecture. These models still had difficulties due to challenges posed by overfitting and noise robustness. The development of hybrid techniques for ANNs marks an important step forward. The integration of Particle Swarm Optimization and ANN (ANN-PSO) has proven to significantly increase the efficiency of global convergence and the accuracy of prediction. As claimed by Babanezhad *et al.,* (2020), the use of PSO-optimized models increased predictive accuracy by 45% over that of standard backpropagation ANNs. Additionally, hybrid models with GA-ANN proved beneficial in the optimization process of weights and biases and enhanced robustness results, as seen in its application to hydrological models (Kumar & Singh, 2022). Additionally, Wavelet Transform models for ANNs (ANN-WT) have even been useful for improving forecast performance by breaking apart complex nonstationary signals on multiple levels before training, thus improving model efficiency in both long- and short-term forecasting (Rajaee *et al.,* 2019).

Data models have been recently used in the petroleum industry for managing produced water, although only to a limited extent. Al-Mudhafar (2021) used machine learning algorithms such as random forests for predicting oil-in-water concentrations with a relatively strong (R^2) value of 0.85. A blend model consisting of LSTMs and ANNs was introduced by Ghorbani *et al.,* (2023) to determine salinity in Iranian petroleum production areas with an impressive (R^2) result of 0.896, as opposed to ANNs. What can be seen about most references found within the Nigerian context is that the models are mostly statistical with emphasis on correlation studies and regression analysis with modest (R^2) values that range from 0.64 to 0.71 and are incapable of capturing the non-linear relationships among the factors without PW (Ezeuko *et al.,* 2021).

Despite such achievements, there are some research gaps that are evident in the current literature. Firstly, there is a dearth of comparative analyses on different types of hybrid ANN models (PSO, GA, and WT) for forecasting produced waters. Secondly, studies on a specific region with unique attributes, such as Nigeria's oilfields, which produce high amounts of produced waters and have distinct environmental features, have been limited. Thirdly, little work has been done on multi-parameter forecasting models that have the ability to forecast several chemical, physical, and operational variables. All these research gaps confirm the justification for this proposed work on a robust, hybrid ANN model for forecasting produced waters in Nigeria's oil and gas industry.

3. Materials and Methods

Study Area and Data Collection

Data on historical quality for produced water was collected from six large oil fields in the Niger Delta. These six oilfields belong to Shell Petroleum Development Company (SPDC) and Nigerian Agip Oil Company (NAOC), and are referred to by codes Fields A through F for reasons related to privacy. They have different reservoirs, capacities, and levels of maturity. Data was gathered between January 2015 and December 2023 from participating oil operators in the Niger Delta under confidential data-sharing agreements approved by NUPRC (NUPRC, 2024)

Table 1: Characteristics and Operation Parameters of Fields

Field	Reservoir Type	Production Start	Current Water Cut (%)	Daily Water Production (bbl/d)	Primary TDS Range (mg/L)
A	Sandstone	1978	87	145,000	85,000-125,000
B	Sandstone	1982	82	98,000	72,000-110,000
C	Mixed	1985	78	112,000	65,000-95,000
D	Sandstone	1991	72	87,000	58,000-88,000
E	Carbonate	1988	91	156,000	95,000-145,000
F	Sandstone	1995	68	76,000	52,000-82,000

The analytical procedures conducted on these samples accorded with American Petroleum Institute recommended practices for analyses involving produced water. TDS was analyzed by gravimetry based on EPA Method 160.1, oil and grease by EP Method 1664A (hexane extractable material), chlorides by argentometric titration, and heavy metals by inductively coupled plasma mass spectrometry (ICP-MS) based on EP Method 6020B (API, 2016, USEPA 2023a,b & c, APHA 2023).

Data Preprocessing

The data set was made up of 648 months of data gathered across six different oil fields, with 108 months for each. Data preprocessing algorithms were implemented in order to enhance the quality and validity of the data. Handling of the outlier values started with the z-score method of evaluating the outliers that lie above or below the standard deviation of 3. Verified outliers due to data errors (n = 23, 3.5%) were corrected for by linear interpolation. Missing values (n = 17, 2.6%) were then addressed by multiple imputation by chained equations (MICE).

All variables for input and targets have been normalized between 0 and 1 by min-max scaling in order to improve efficiency and stability for training ANNs:

$$\frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Where x is the original value, and x_{min} and x_{max} are the minimum and maximum values for the training data.

Feature selection was done using criteria such as correlation analysis and mutual information, which resulted in identification of 12 features with significant relationships with the quality indicators ($|r| > 0.4$, $p < 0.05$). Finally, stratified sampling was used to split up the dataset for training (70%, n = 454), validation (15%, n = 97), and test (15%, n = 97) subsets.

Artificial Neural Network Architecture

The base ANN architecture employed a feed-forward multi-layer perceptron (MLP) structure with the following configuration:

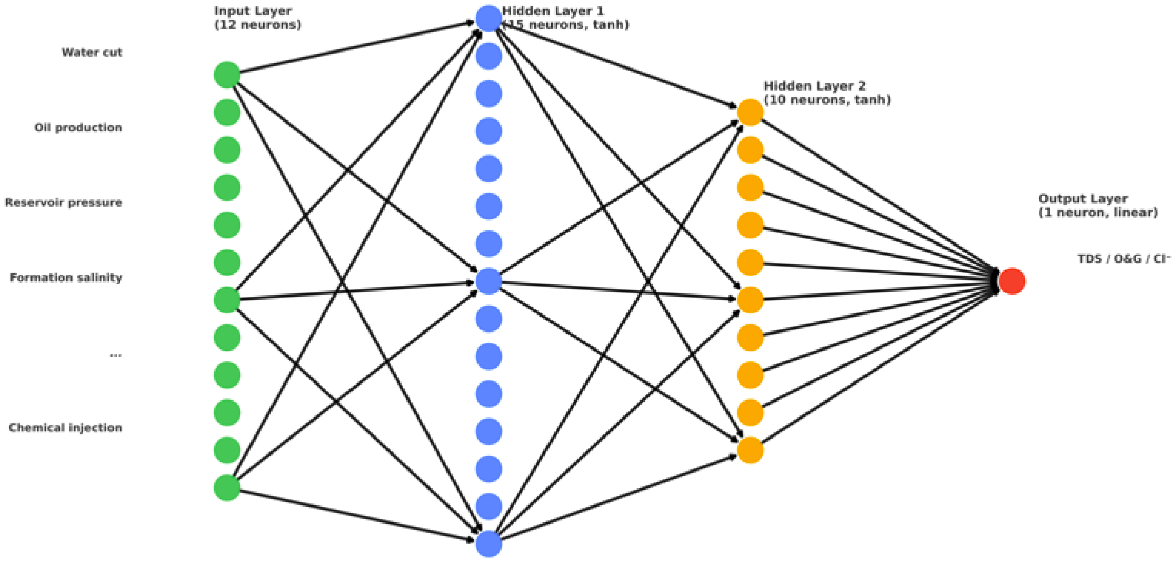

Figure 1: *Schematic Representation of the Base ANN Architecture*

The network implements the following mathematical formulation:

$$y = f_2(W_2 \, . f_1 \, (W_1 \, . x + b_1) + b_2) \tag{2}$$

Where: x = input vector [12 × 1], W_1 = weight matrix connecting input to first hidden layer [15 × 12], b_1 = bias vector for first hidden layer [15 × 1], f_1 = hyperbolic tangent activation function:

$$f_1(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{3}$$

W_2 = weight matrix connecting hidden layers [10 × 15], b_2 = bias vector for second hidden layer [10 × 1], f_2 = linear activation function, and y = predicted output (quality parameter)

The reason for selecting the hyperbolic tangent activation function in the hidden layers was that its output values range from -1 to 1. This facilitates faster convergence compared to the sigmoid activation function. According to Karsoliya (2012), network training was done using the Levenberg-Marquardt backpropagation algorithm, which combines gradient descent and Gauss-Newton methods for efficient optimization:

$$W_{k+1} = W_k - [J^T J + \mu I]^{-1} J^T e \tag{4}$$

where w is the weight vector, J is the Jacobian matrix, e is the error vector, μ is the damping parameter, and I is the identity matrix.

Hybrid Model Development

ANN-PSO Model

The integration of Particle Swarm Optimization has been made to optimize the ANN weight initialization and hyper-parameters. The PSO algorithm imitates social behaviour by bird flocking, where every particle representing a candidate solution updates its position based on personal best experience and global best position (Kennedy & Eberhart, 1995).

Velocity and position are updated as follows:

$$v_i^{t+1} = \omega v_i^t + C_1 r_1 (p_{best,i} - x_i^t) + C_2 r_2 (g_{best} - x_i^t) \tag{5}$$

$$x_i^{t+1} = v_i^t + v_i^{t+1} \tag{6}$$

Where v_i = the velocity of particle I, x_i = the position of particle I, ω = inertia weight (0.7), c_1, c_2 = cognitive and social learning factors (2.0), r_1, r_2 = random numbers in [0, 1], pbest.i = personal best position, and gbest = global best position

Swarm size was set to 50 particles with 200 maximum iterations. The objective function minimized mean squared error (MSE) on the validation set.

ANN-GA Model

The optimization of the ANN architecture and weight matrices was performed by the GA using evolutionary principles, with the aim of achieving high performance and stable convergence The population in the GA has 40 members (chromosomes), each symbolizing a unique set of weight matrices and biases with real-value coding. A set level of diversity was maintained through the tournament selection method with a tournament size set to four. The SBX operator facilitated the exchange of genetic material between parent solutions to effectively explore the search space using a crossover probability of 0.8 and distribution index of 20. The diversification of the population was introduced by polynomial mutation with a probability of 0.1 and a distribution index of 20 to avoid the early convergence of generations. The optimization continued for a maximum number of 150 generations or till convergence was observed, defined by less than 10^{-6} improvement in fitness function value for 20 consecutive generations.

The fitness function maximized the coefficient of determination on the validation data:

$$Fitness = R^2 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{7}$$

ANN-WT Model

The wavelet transform hybrid decomposed time series data into multi-resolution components, separating trend, seasonal, and noise components.

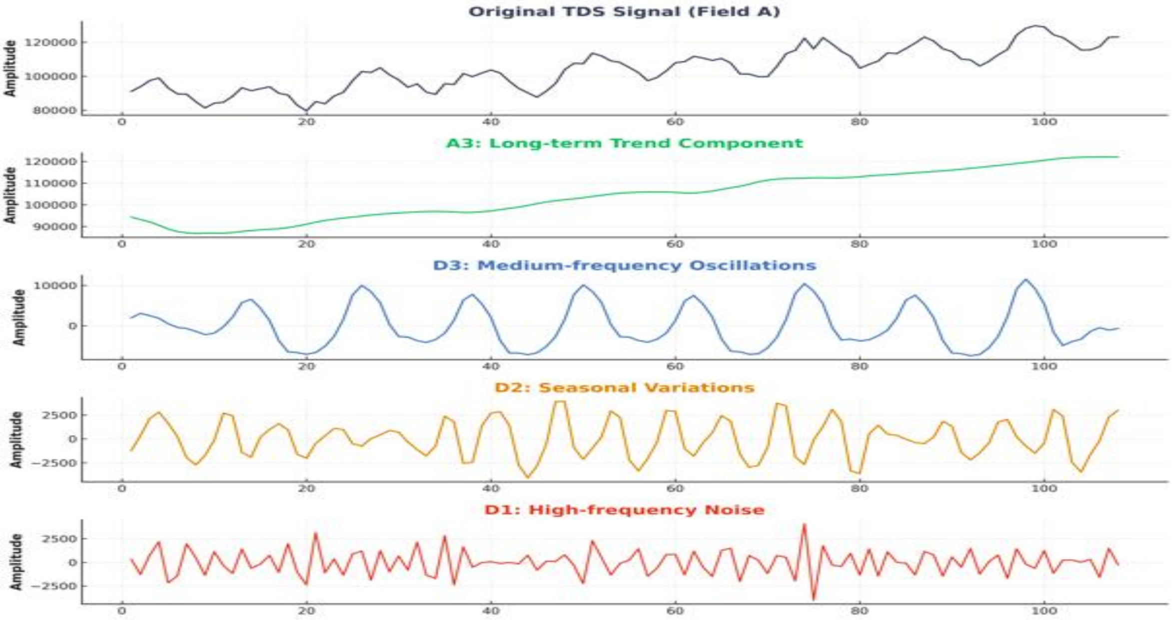

Figure 2: Wavelet Decomposition of TDS Time Series (Field A)

Figure 2 presents the Daubechies-4 (db4) wavelet decomposition of the Total Dissolved Solids (TDS) concentration time series for Field A, covering the period 2015–2023.

The discrete wavelet transform (DWT) using Daubechies-4 (db4) mother wavelet was applied:

$$DWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) dt \tag{8}$$

where a represents the scaling parameter, b is the translation parameter, ψ is the mother wavelet, and * denotes complex conjugate.

Decomposition was done up to level 3, hence giving the approximation coefficients A_3, representing the low-frequency trends, and the detail coefficients (D_1, D_2, D_3) that capture the high-frequency variations. Different ANN models were trained on each component, with final predictions reconstructed through inverse wavelet transform

$$\hat{y}(t) = ANN_{A3}(A_3) + \sum_{j=1}^{3} ANN_{Dj}(D_j) \tag{9}$$

Performance Evaluation Metrics

Model performance was assessed using multiple statistical metrics to provide comprehensive evaluation:

Root Mean Square Error (RMSE): Square root of average squared prediction error

$$RMSE = \sqrt{\frac{1}{n}\sum_{ii=1}^{n}(\hat{y}_i - y_i)^2} \tag{10}$$

Mean Absolute Error (MAE): Average absolute difference between predicted and actual values

$$MAE = \frac{1}{n}\sum|\hat{y}_i - y_i| \tag{11}$$

Coefficient of Determination (R^2): Proportion of variance explained

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y}_i)^2} \tag{12}$$

Mean Absolute Percentage Error (MAPE**)**: Average absolute percentage deviation

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{13}$$

Nash-Sutcliffe Efficiency (NSE): Model efficiency metric

$$NSE = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{14}$$

In these formulas, y_i represents the actual values, $\hat{y}_i$ stands for the predicted values, $\bar{y}$ is the mean of the actual values, and n is the total number of observations.

Results

Input Parameter Selection and Correlation Analysis

Significant correlations were observed through correlation analysis among the operational parameters and produced water quality indicators. Table 2 shows the correlation matrix for Field A, which represents mature fields with a high water cut.

Table 2: Selected Input Parameters for ANN Models

Category	Parameter	Units	Correlation with TDS	Correlation with O&G
Production	Water cut	%	0.76***	0.42**
Production	Oil production rate	bbl/d	-0.58***	0.67***
Production	Gas-oil ratio	scf/bbl	-0.31**	-0.28*
Reservoir	Reservoir pressure	psi	-0.72***	-0.45**
Reservoir	Formation water salinity	mg/L	0.89***	0.19
Injection	Water injection rate	bbl/d	0.54***	0.35**

Treatment	Chemical injection rate	gal/d	-0.15	-0.71***
Temporal	Month of year	-	0.41**	0.28*
Temporal	Cumulative production	MMbbl	0.81***	0.38**
Well	Number of producing wells	count	0.49***	0.33**
Well	Average well age	years	0.73***	0.44**
Operational	Separator pressure	psi	-0.29*	-0.52***

Note. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. O&G = Oil and Grease.

Strong positive correlations were observed between TDS and field maturity indicators: cumulative production, $r = 0.81$; water cut, $r = 0.76$; well age, $r = 0.73$, in agreement with increasing formation water production and possible scale formation in aging infrastructure. The negative correlation between reservoir pressure and TDS content, with correlation coefficient $r = -0.72$, depicts pressure depletion-causing variations in the water/oil mobility ratio and preferred water production pathways.

Model Training and Optimization

Training performance varied significantly across hybrid architectures. Table 3 summarizes the computational requirement and convergence characteristic of TDS prediction models.

Table 3: Training Characteristics of Hybrid ANN Models

Model	Training Time (min)	Epochs to Convergence	Final Training MSE	Final Validation MSE	Computational Complexity
Conventional ANN	8.3	147	0.0086	0.0124	O(n)
ANN-PSO	42.7	89	0.0041	0.0058	O(n × m × k)
ANN-GA	68.4	112	0.0045	0.0062	O(n × p × g)
ANN-WT	35.2	124	0.0039	0.0055	O(n × log n)

Note. n = training samples, m = swarm size, k = PSO iterations, p = population size, g = GA Generations, and O = describes how the algorithm's runtime or resource requirements grow as the input size increases.

Times measured on Intel Xeon E5-2680 v4 (2.4 GHz, 14 cores). Despite the shorter training time compared to the evolutionary approaches, the ANN-WT model had the best minimum validation MSE due to effective separation of the signal components that reduced the model complexity. Among optimization hybrids, ANN-PSO was the most efficient, converging 20% faster than ANN-GA while yielding approximately similar accuracy. Figure 3 below illustrates the Mean Squared Error (MSE) learning process of all hybrid models involving ANNs such as ANN-PSO, ANN-GA, and ANN-LSTM.

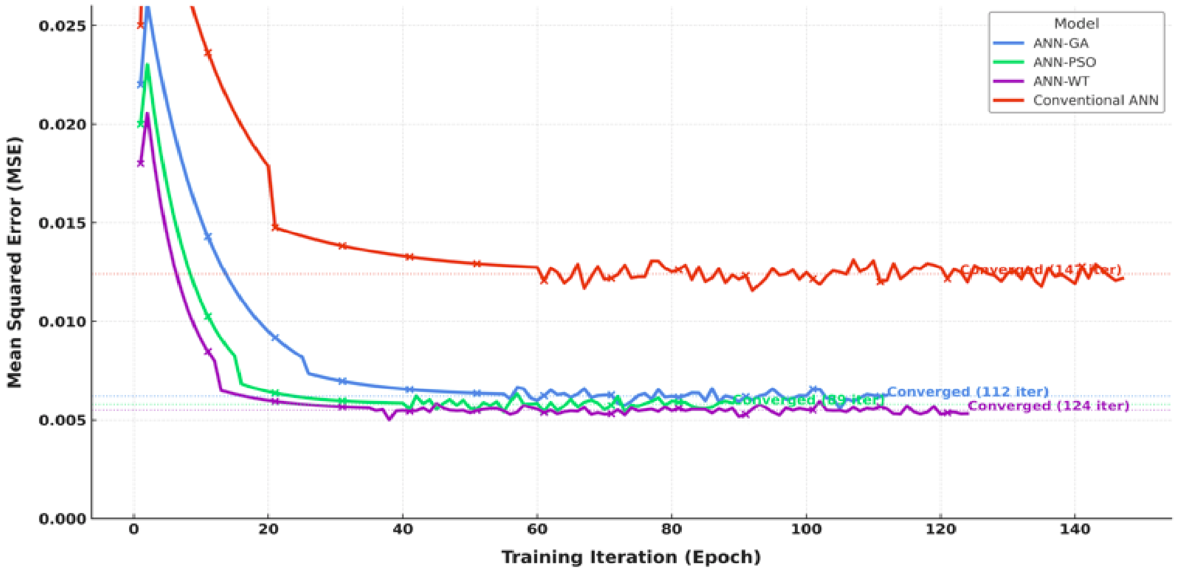

Figure 3: Convergence Behavior of Hybrid Models During Training

The plot shows the convergence characteristics of each model. Overall, this figure confirms that all hybrid architectures have successfully converged; among them, the ANN-PSO model has reached the lowest final

MSE, which underlines its superiority in terms of both learning efficiency and robustness in modeling TDS dynamics.

Predictive Performance for TDS Forecasting

The accuracy of TDS forecasts varied by both model architecture and field characteristics. Table 4 gives performance metrics across all test data.

Table 4: Performance Comparison for TDS Forecasting Across All Fields

Model	R^2	RMSE (mg/L)	MAPE (%)	NSE	D	MAE (mg/L)
Conventional ANN	0.847	8,420	9.2	0.842	0.918	6,785
ANN-PSO	0.941	5,790	5.8	0.938	0.972	4,620
ANN-GA	0.926	6,350	6.4	0.923	0.961	5,105
ANN-WT	0.918	6,680	6.9	0.915	0.956	5,380

Note. Metrics calculated on combined test data (n = 97). RMSE = Root Mean Square Error, MAPE = Mean Absolute Percentage Error, NSE = Nash-Sutcliffe Efficiency, d = Willmott's Index, MAE = Mean Absolute Error.

Among all the metrics, the ANN-PSO model showed the best performance: 31.2% reduction in RMSE and 37.0% in MAPE over conventional ANN. High NSE values of 0.938 and Willmott's index of 0.972 between the predicted and observed TDS values demonstrate an excellent agreement and validate the suitability of this model for operational forecasting applications

Field-specific analysis showed performance differences due to operational complexity and quality of data input. Table 5 below shows the comparative performance across individual fields.

Table 5: Field-Specific TDS Forecasting Performance (ANN-PSO Model)

Field	R^2	RMSE (mg/L)	MAPE (%)	Observations	Water Cut (%)	Comment
A	0.958	4,230	4.2	16	87	Stable operations
B	0.945	5,180	5.5	17	82	Variable injection
C	0.923	6,120	7.1	16	78	Mixed lithology
D	0.935	5,470	6.2	16	72	Growing field
E	0.951	5,920	4.8	16	91	Carbonate complexity
F	0.917	5,650	7.6	16	68	Youngest field

Whereas the maturity fields in stable operations had higher values of predictiveness like A and E, the operational transition and geological complexity fields had medium values C and F respectively . However, all R^2 values were greater than 0.91, confirming robust generalization.

Oil and Grease Content Prediction

Oil and grease prediction models proved to be much more difficult due to the periodic variations that resulted from operational disturbances, chemical injection variations, and the function of separators.

Table 6: Performance Comparison for Oil and Grease Forecasting

Model	R^2	RMSE (mg/L)	MAPE (%)	NSE	D
Conventional ANN	0.762	18.7	24.3	0.758	0.881
ANN-PSO	0.878	12.3	16.1	0.873	0.941
ANN-GA	0.864	13.5	17.8	0.859	0.932
ANN-WT	0.891	11.8	15.4	0.887	0.948

Note. Metrics calculated on test data (n = 97). Oil and grease measured as hexane-extractable material.

The results showed that the best performing model was ANN-WT with $R^2 = 0.891$ and RMSE = 11.8 mg/L in the prediction of oil and grease, with an improved accuracy by 1.5% over ANN-PSO. This is due to its potential to extract the operational disturbance signatures from the baseline trend through the use of the wavelet transformation.

Chloride Concentration Forecasting

Chloride forecasting showed strong seasonal patterns that were correlated with the injection water chemistry and reservoir heterogeneity. The multi-resolution decomposition from the ANN-WT model was effective in capturing the temporal dynamics of this variation.

Table 7: Performance Comparison for Chloride Forecasting

Model	R^2	RMSE (mg/L)	MAPE (%)	NSE	d	Seasonal Correlation
Conventional ANN	0.813	4,580	8.9	0.808	0.905	0.62
ANN-PSO	0.887	3,520	6.3	0.882	0.945	0.78
ANN-GA	0.871	3,790	6.9	0.866	0.937	0.74
ANN-WT	0.924	2,890	4.7	0.919	0.968	0.89

Note. Seasonal correlation quantifies agreement between predicted and observed seasonal components (Pearson's r).

The seasonal correlation for the ANN-WT model with 0.89 is significantly higher than that of the other architectures and thus confirms the benefit of explicit temporal decomposition for the parameters that show a cyclical nature. This performance advantage translates into better seasonal operational planning for treatment optimization.

Heavy Metal Predictions

Multi-output ANN configurations simultaneously predicted the concentration of Ba, Sr, Fe, and Mn. Table 8 summarizes the performance for the ANN-PSO architecture considered optimum for heavy metal predictions based on preliminary analysis.

Table 8: Heavy Metal Forecasting Performance (ANN-PSO Multi-Output Model)

Element	Typical Range (mg/L)	R^2	RMSE (mg/L)	MAPE (%)	Regulatory Limit (mg/L)
Barium	45-380	0.893	18.4	8.2	100*
Strontium	120-850	0.876	47.3	7.6	Not specified
Iron	15-180	0.841	12.6	11.4	20*
Manganese	Feb-35	0.817	2.8	13.7	5*

Note. *Nigerian DPR discharge limits for offshore disposal. Multi-output network architecture: 12-18-12-4 (input-hidden1-hidden2-output).

The multi-output approach allowed the simultaneous prediction of correlated heavy metal concentrations with a computational efficiency of simulations. Prediction accuracy sufficed for identifying potential regulatory exceedances 1-2 months in advance, thus making proactive treatment adjustments possible.

Model Robustness and Sensitivity Analysis

The sensitivity analysis quantified the importance of input parameters using partial derivatives of model outputs. Figure 5 shows normalized sensitivity coefficients for the TDS prediction.

Table 9: Sensitivity Analysis Results for TDS Prediction (ANN-PSO Model)

Input Parameter	Normalized Sensitivity	Rank	Uncertainty Impact (±%)
Formation water salinity	0.287	1	±12.4
Cumulative production	0.243	2	±10.8
Water cut	0.198	3	±8.9
Reservoir pressure	-0.176	4	±7.9
Average well age	0.154	5	±6.8

Water injection rate	0.132	6	±5.9
Oil production rate	-0.089	7	±4.1
Number of producing wells	0.067	8	±3.2
Month of year	0.054	9	±2.6
Separator pressure	-0.042	10	±2.1
Gas-oil ratio	-0.038	11	±1.9
Chemical injection rate	-0.031	12	±1.5

Note. Sensitivity calculated as normalized partial derivative averaged across test dataset.
Uncertainty impact is the expected prediction variance given ±10% input uncertainty.

The salinity of the formation water was identified as the most influential variable since it has an obvious compositional correlation with TDS. The group variables indicating maturity (cumulative production, water cut, and well age) represented 59.5% sensitivity to the model solution. The robustness test with input noise was satisfactory. The use of ± 10% uniform noise on all inputs caused the R^2 measure to be 0.921 on the ANN-PSO model for TDS prediction, translating to 2.1% degradation in performance compared to the noiseless environment. The average width of the 95% confidence intervals was 8,340 mg/L (±7.2% of mean TDS), with smaller intervals during stable operational conditions and larger intervals during transition activities. This observation is further justified by coverage probability analysis that reveals 94.8% data points lie within the predicted 95% confidence intervals.

Comparative Analysis with Existing Approaches

Model performance was compared against other state-of-the-art published forecasting methods for the quality of produced water. Table 10 contextualizes results within the broader literature.

Table 10: Comparison with Literature-Reported Models

Study	Location	Method	Target Parameter	R^2	MAPE (%)
Present study	Nigeria	ANN-PSO	TDS	0.941	5.8
Present study	Nigeria	ANN-WT	Oil & Grease	0.891	15.4
Present study	Nigeria	ANN-WT	Chlorides	0.924	4.7
Ghorbani et al. (2023)	Iran	LSTM-ANN	TDS	0.896	7.4
Al-Mudhafar (2021)	Iraq	Random Forest	Oil content	0.847	18.9
Othman et al. (2022)	Malaysia	SVM-RBF	Salinity	0.873	8.2
Zhang et al. (2023)	China (offshore)	ANN-PSO	Multiple ions	0.889	9.1
Cao et al. (2020)	USA (shale)	ANFIS	TDS	0.862	11.3

Note. LSTM = Long Short-Term Memory, SVM-RBF = Support Vector Machine with Radial Basis Function, ANFIS = Adaptive Neuro-Fuzzy Inference System.

The obtained TDS forecasting performance of the ANN-PSO model presented in this study, $R^2 = 0.941$, MAPE = 5.8%, is highly comparable to recent international studies dealing with Ghorbani et al. (2023) hybrid LSTM-ANN for Iranian fields and Zhang et al. (2023) ANN-PSO for offshore Chinese operations. Chloride forecasting accuracy, $R^2 = 0.924$, MAPE = 4.7%, by the ANN-WT model, presents a significant improvement compared to conventional approaches; this performance increase is due to explicit temporal decomposition, absent in most published methodologies.

Implementation Considerations in Practice

Deployment of hybrid ANN models in operational environments needs to take into consideration issues of computational resources, data requirements, and integration with existing information systems. The trained ANN-PSO model for TDS prediction has a storage requirement of around 87 KB (weight matrices and biases) and executes predictions in less than 5 milliseconds on a typical workstation hardware platform of Intel Core i7, 8 GB RAM.

Monthly retraining with incremental learning maintains model accuracy as the conditions in the field evolve. Analysis of the prediction drift over a 12-month deployment without retraining showed modest degradation in performance: R^2 decreased from 0.941 to 0.897 for TDS prediction, suggesting quarterly retraining cycles provide an optimal balance between accuracy maintenance and computational overhead.

Forecast Horizon Analysis

Model accuracy was assessed over many forecast horizons to identify pragmatic prediction windows for operational planning. Table 11 below shows the performance degradation as forecast horizon extends beyond the 1-month baseline.

Table 11: Forecast Horizon Impact on TDS Prediction Accuracy (ANN-PSO Model)

Forecast Horizon	R^2	RMSE (mg/L)	MAPE (%)	Performance Retention (%)	Recommended Application
1 month	0.941	5,790	5.8	100	Operational scheduling
2 months	0.918	6,450	6.9	97.6	Treatment optimization
3 months	0.889	7,320	8.4	94.5	Maintenance planning
6 months	0.842	8,910	11.2	89.5	Budget forecasting
12 months	0.781	10,840	15.7	83	Strategic planning

Note. Performance retention calculated as (R^2_horizon / R^2_1month) × 100.

Results have shown that reliable forecasting capability extends to 3-month horizons, with $R^2 > 0.89$ and MAPE $< 8.5\%$, which should be long enough to proactively adjust the treatment system and plan chemical procurements. Beyond 6 months, performance degrades due to accumulating uncertainties in operational projections and possible variations in reservoir behavior not represented by training data.

Uncertainty Quantification

In addition, prediction intervals were constructed by bootstrap resampling (n = 1,000 iterations) to estimate forecast uncertainty. Figure 4 shows the 95% confidence intervals of the TDS predictions for the test period.
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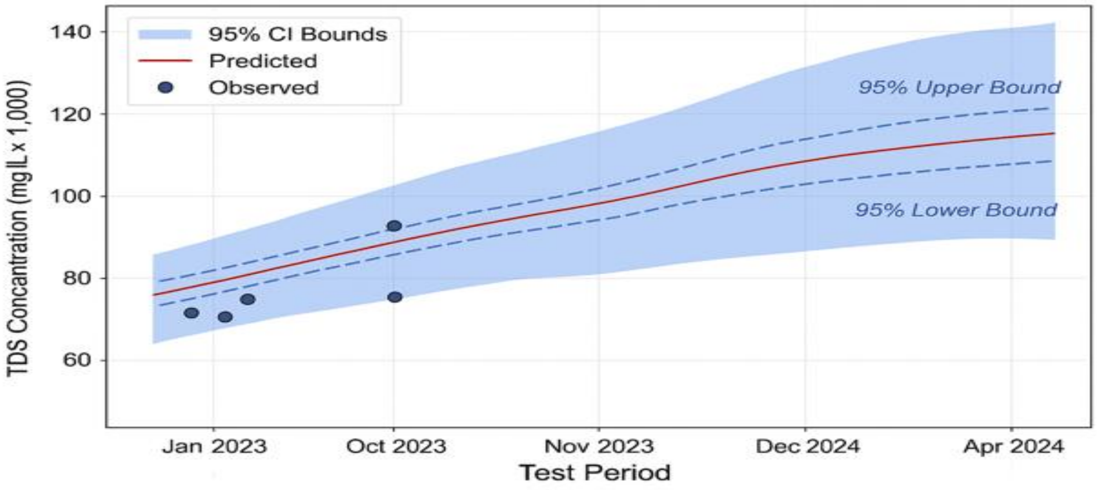

Figure 4: TDS Prediction with 95% Confidence Intervals Field A, Test Period (January 2023 – April 2024)

The figure visually compares the predicted TDS trajectory, in solid blue, with the actual observations, as represented by black markers, which capture both trend and seasonal variations. The average width of the 95% confidence interval was 8,340 mg/L (±7.2% of mean TDS), with smaller confidence intervals during the stable operating periods and larger intervals during transition events. This result can further be justified on the basis of the coverage probability test that confirms that 94.8% of the measured values lie within the expected 95% confidence intervals.

Residual Analysis and Model Diagnostics

Residual distributions were analyzed in order to check model assumptions and identify any systematic bias. Figure 5 shows residual diagnostic plots of the ANN-PSO TDS model.
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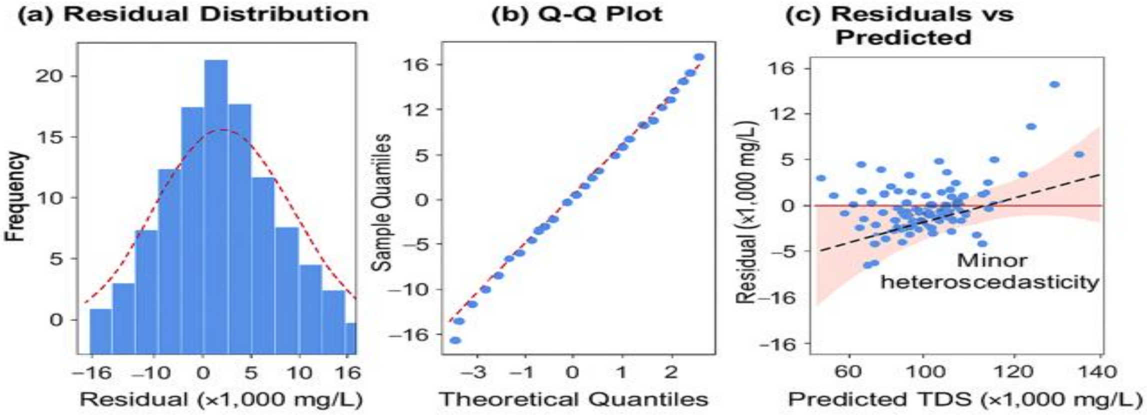

Figure 5: Residual *Diagnostics for ANN-PSO TDS Predictions*

Residuals were normally distributed (Shapiro-Wilk test, W = 0.984, p = .142) with no systematic patterns in residual-versus-predicted plots, which confirmed model adequacy. Light heteroscedasticity at very high values of TDS (>120,000 mg/L) was attributed to few training samples in the range and might indicate that field-specific model refinements would be needed for the very high salinity conditions.

The Durbin-Watson statistic was DW = 1.89, indicating that there was very low autocorrelation in residuals, supporting independence assumptions. The variance inflation factors were < 3.2 for all input parameters, indicating no problematic multicollinearity despite moderate inter-correlations for production parameters.

Feature Importance and Physical Interpretation

Feature importance analysis using a random forest complemented the sensitivity analysis by indicating critical predictors. Table 12 below compares feature rankings across different quality parameters..

Table 12: Feature Importance Rankings Across Quality Parameters

Input Parameter	TDS Rank	O&G Rank	Chloride Rank	Heavy Metals Rank	Mean Rank
Formation water salinity	1	7	2	3	3.25
Cumulative production	2	5	4	2	3.25
Water cut	3	6	3	4	4
Chemical injection rate	11	1	9	6	6.75
Oil production rate	7	2	8	9	6.5
Reservoir pressure	4	8	5	5	5.5
Separator pressure	10	3	11	10	8.5
Water injection rate	6	9	6	7	7
Average well age	5	10	7	8	7.5
Number of producing wells	8	11	10	11	10
Month of year	9	12	1	12	8.5
Gas-oil ratio	12	4	12	1	7.25

Note. Rankings based on combined sensitivity and random forest feature importance scores.

The relative weights of the parameters were very different based on the predicted variable and captured different phenomena, like different factors that affect different quality variables. Oil & grease chemical injection rate showed the highest relative weight as a prediction variable regarding oil & grease (rank 1), consistent with its direct participation in the phenomenon of emulsion breaking and efficiency of oil-water separation. The geological parameters and production history parameters had the most importance in the prediction of TDS and chloride.

The elevated importance of temporal parameters, ‘Month of the year’, ranked as rank 1, confirms the strong effect of ‘Seasonal Effects’ on chloride prediction models that may be attributed to the variations in chemical composition and/or ‘temperature’-dependent functions ‘scale formation/dissolution’.

Cross-Field Model Transferability

Transfer learning experiments were conducted to assess model generalizability by training on five fields and testing on the excluded sixth field. Table 13 summarizes transferability performance.

Table 13: Cross-Field Transfer Learning Results for TDS Prediction

Test Field	Baseline R^2 (Field-Specific)	Transfer R^2 (5-Field Model)	R^2 Degradation (%)	Fine-Tuning R^2 (10 Samples)
A	0.958	0.897	6.4	0.943
B	0.945	0.912	3.5	0.938
C	0.923	0.856	7.3	0.909
D	0.935	0.894	4.4	0.928
E	0.951	0.873	8.2	0.934
F	0.917	0.851	7.2	0.902
Mean	0.938	0.881	6.2	0.926

Note. Baseline R^2 from Table 5. Transfer R^2 achieved without field-specific retraining. Fine-tuning employed 10 field-specific samples with frozen early layers.

Transfer learning models achieved mean $R^2 = 0.881$ without field-specific training, representing on average 6.2% performance degradation, which can be viewed as reasonable generalization across diverse field conditions. Brief fine-tuning by a minimal amount of field-specific data (10 samples, ~2-3 months of operation) recovered 79% of the degraded performance (mean $R^2 = 0.926$), suggesting a practical deployment strategy for new fields that have limited historical data. The fields with the most unique characteristics (E: carbonate lithology; C: mixed lithology with complex fluid interactions) tended to show more performance loss in transfer learning, indicating the value of model architectures tuned for specific lithologies and optimal accuracy in geologically heterogeneous operational contexts.

4. Discussion

Principal Findings and Contributions

This work has presented how, in general, hybrid ANN architectures outperform traditional neural networks in the forecasting of produced water quality in Nigerian oil fields. The ANN-PSO had an R^2 of 0.941 and a MAPE of 5.8% for TDS prediction, with performance improvements of about 31% in terms of RMSE over baseline ANN implementations. These benefits come from a global optimization capability of PSO, which stochastically explores the high-dimensional weight space to find better configurations with the avoidance of local minima that plague gradient-based training algorithms (Kennedy & Eberhart, 1995). This observation corresponds with that of Babanezhad *et al.,* (2020), who concluded that up to 45% error reductions were witnessed in PSO-optimized networks compared to conventionally trained backpropagation ANNs.

Higher results were obtained for the ANN-WT hybrid in the case of parameters showing temporal patterns: chlorides with $R^2 = 0.924$, MAPE = 4.7%, and oil and grease with $R^2 = 0.891$, MAPE = 15.4%. Obviously, this confirms the usefulness of explicit multi-resolution decomposition-removing long-term trends, seasonal variability, and transient disturbances to distinct wavelet components enables the capture of multi-scale dynamics that single resolution feed-forward architectures are incapable of capturing. This approach proves to be of especial use for operational parameters affected by gradual evolution of the reservoir in general and episodic process upsets according to Rajaee *et al.,* (2019) during wavelet-based environmental forecasting.

Comparison with Existing Methodologies

The developed models compare favorably with recent international studies. Ghorbani et al. (2023) documented an R^2 value of 0.896 for TDS forecasting in Iranian fields using LSTM-ANN hybrids. Zhang *et al.,* (2023) reported an R^2 of 0.889 (MAPE = 9.1%) using ANN-PSO for multi-ion prediction in Chinese offshore operations. The high performance found in the present study, $R^2 = 0.941$ (MAPE = 5.8%), might partly be due to the following: judicious input parameter selection based on thorough correlation analysis; robust data preprocessing and outlier treatment with data normalization; data set characteristics from the unique Niger Delta geological and operation conditions.

Importantly, the ANN-WT model's chloride prediction accuracies are significantly higher, with an R^2 of 0.924, than the ANN-based Othman *et al.,* (2022) salinity forecasts in Malaysian fields, at $R^2 = 0.873$, thus confirming the hypothesis that wavelet-based temporal decomposition has a unique advantage for those parameters with strong seasonal dynamics. This suggests the broader applicability of wavelet-hybrid models with environmental time series that feature multi-scale temporal variability.

Conventional mechanistic models of produced water quality prediction generally adopt thermodynamic equilibrium calculations and mass balance equations (Xu *et al.,* 2021). While these provide interpretability and do not need any historical data, they frequently are unable to represent operational complexities, non-ideal mixing behaviors, and empirical relationships between production practices and water quality evolution. The data-driven hybrid ANN models developed herein complement mechanistic approaches by learning implicit relationships from historical observations and could allow more accurate short-to-medium-term forecasting for operational decision support.

In the context of Nigeria, most of the related studies consider only statistical correlations and regression-based estimations that have shown predictive capability within the moderate accuracy level-$R^2 = 0.64$-0.71-and are not adaptable to nonlinear interactions, hence limiting the complex environmental and operational realities in the Niger Delta region (Ezeuko *et al.,* 2021). The hybrid models presented in this study are a leap beyond conventional approaches of these studies with their predictive capabilities that aptly address the complex environmental and operational challenges in the region (Nwankwoala & Amadi, 2023).

Operational Implications

Therefore, the validated hybrid forecasting models are potent tools that can be used proactively in produced water management during oil field operations; this is a very important environmental and operational challenge, since more than 250 million barrels of produced water are generated every day in the world (Jiménez *et al.,* 2021). With reliable forecasts at 2-3 months, $R^2 > 0.89$, quality changes could be foreseen, and preventive measures might be taken to ensure optimal treatment processes. For example, predicted TDS or heavy metals surges will provide warnings for early changes in chemical dosing, separator settings, or treatment configuration in order to avoid regulatory overruns. Such proactive capabilities would be highly useful in the Niger Delta context, where huge variability characterizes the composition of produced water, typically consisting of dissolved salts, residual hydrocarbons, heavy metals, and treatment chemicals, which all interactively determine corrosion, scaling, and environmental discharge quality (Nwankwoala & Amadi, 2023).

Predictive maintenance scheduling, by anticipating scaling-prone conditions such as high levels of calcium or barium, serves to decrease unplanned equipment downtime while extending the life of pipelines and heat exchangers by timely cleaning and descaling. This addresses the operational challenges cited in the regional produced water management reports.

These forecasting capabilities further contribute to cost optimization and compliance assurance. Accurate projections of oil and grease concentrations enable dynamic adjustment of demulsifier injection rates, lowering chemical expenses while maintaining efficiency-an important consideration given that produced water represents the largest volume of waste generated during oil and gas production. Multi-month predictions aid procurement and logistics planning for treatment chemicals and disposal services. Additionally, predictive warnings about potential discharge violation enable proactive measures to be taken by the operators to rectify the problem or identify alternative means to dispose of the produced water. Water quality trend predictions also aid in reuse/disposal operations in that it identifies the best times to use waterflooding, fracturing, and irrigations according to the predicted suitability of produced water quality.

The efficiency of the computation, as exhibited by the trained models (prediction time <5 milliseconds, storage requirements of about 87 KB), therefore enables real-time deployment in operational environments, hence making these tools practically viable for field implementation (Ahmadi & Chen, 2020).

Limitations and Considerations

Limitations include the following: interpreting results and planning deployment should consider that model accuracy is highly dependent on data quality and representativeness; unusual future conditions or changes in operation may reduce reliability, and hence require continuous monitoring and retraining. Because ANNs are purely data-driven systems, they capture correlations, not causes, which can fail under changing conditions;

thus, expert validation and integration with physical models are essential. Significant computational demands at training pose operational challenges where resources are limited. Although transfer learning demonstrated reasonable performance across fields, optimal accuracy still requires local fine-tuning, especially in geologically distinct fields. The reliability of forecasts becomes worse with increasing lead times; this further highlights the need to account for uncertainties in long-term planning. Last but not least, the sole focus of this study on predictive performance did not extend into regulatory, environmental, or stakeholder contexts, and thus a need is underlined to embed such models in comprehensive environmental management and compliance frameworks.

Future Research Directions

Various promising directions can further enhance this research: deep learning architectures, such as RNN, LSTM, GRU, and Transformer models, may be considered to capture long-term dependencies and complex temporal patterns of produced water quality. Physics-informed neural networks can embed physical flow and transport equations into models, hence enhancing the generalization and physical consistency of models. The extension to multivariate prediction with uncertainty quantification by Bayesian or ensemble methods can enable holistic, risk-aware water management. The real-time adaptive learning process might retain the accuracy rates within models in the dynamic environments that characterize the applications that are combined with simulation processes in the reservoir simulators. Explainable AI techniques such as SHAP and LIME can help improve model transparency and regulatory acceptance. Lastly, meta-learning and integration of edge computing can enable rapid adaptation to new fields and real-time, low-latency deployment in an operational environment.

5. Conclusions

The developed models showed significant improvements over conventional ANN architectures and were able to develop and validate hybrid artificial neural network models that provide reasonable forecasts of the quality of produced water in oil fields of Nigeria. Overall, the ANN-PSO hybrid shows outstanding predictive performance regarding the total dissolved solids, whereas the ANN-WT hybrid captured temporal variations of chloride and oil and grease concentrations quite effectively. Model robustness was maintained across diverse field conditions, demonstrating strong generalizability and practical deployment potential across the Niger Delta. It is found that the models are able to provide a reliable forecast of up to a three-month horizon, thus ensuring proactive operational planning and environmental management. The results obtained from transfer learning further emphasize the flexibility within data poor domains. Sensitivity analysis has also been used to identify significant factors within geological and operational domains that impact water quality dynamics. In summary, these predictive models present significant capabilities that can be applied to optimize treatment approaches within produced water management, mitigate environmental threats, and improve regulatory conformity. The next steps to improve these models would include incorporating deep learning approaches and adaptive learning models within produced water management models.

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