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MODELING DISSOLVED OXYGEN (DO) CONCENTRATION AT KAINJI HYDROPOWER RESERVOIR USING ARTIFICIAL NEURAL NETWORK

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Abstract: The objective of this study was to develop a multilayer perceptron neural network (MLPNN) and radial basic function neural network (RBFNN) model to predict the dissolved oxygen (DO) at some selected locations at the Kainji hydropower reservoir, Nigeria. The neural networks (NN) model was developed using water quality data collected over a six-year period (2010 to 2015). The NN structure was designed and trained using the SPSS neural network toolbox. The input variables to the NN were: pH, temperature, chloride (Cl^-), PO_4^{3-}, NO^{3-}, Fe^{2+}, and electrical conductivity (EC), while the output was the DO. The performance evaluation of the model was carried out using the coefficient of correlation (r), mean square error (MSE) and mean relative error (MRE). A positive correlation was observed between the actual and simulated DO at the four locations. The results of the simulation showed that the application of the NN and multiple regression analysis to predict DO concentration in water gave satisfactory results for all the selected locations using the two NN modeling approaches. Thus it has been demonstrated that NN modeling tools and multiple regression analysis are very efficient and useful for the computation of water quality parameters.

Keywords: *Dissolved oxygen, hydropower reservoir, kainji, neural network and water quality*.

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1.0 Introduction

The concentration of dissolved oxygen (DO) is important for the healthy functioning of aquatic ecosystems and also as a significant indicator of the state of aquatic ecosystems. DO is a parameter frequently used to evaluate the water quality at different reservoirs and watersheds (Kişi and Ay, 2013). The development and current progress of the integration of various artificial intelligence techniques (knowledge-based system, genetic algorithm, artificial neural network and fuzzy inference system) into water quality modeling are now of interest worldwide. Artificial neural networks (ANNs) have been successfully used in the fields of water quality prediction and forecasting.

Palani, Liong and Tkalich (2008) used an ANN application for forecasting water quality in the coastal waters of Singapore. The model was built for a quick assessment and forecasting of selected water quality variables at any location in the domain of interest. The results showed that the model has great potential to simulate water quality variables. Kişi and Ay (2013) used two different ANN models: the multilayer perceptron (MLP) and the radial basis neural network (RBNN) to estimate the DO concentration using various combinations of daily input variables: pH, discharge (Q), temperature (T) and electrical conductivity (EC) for a period of 18 years (1994 to 2011). Statistical parameters such as the root mean square error (RMSE), mean absolute error (MAE) and determination coefficient (R^2) were used to test the results. The ANN results were compared with those of the multiple linear regression (MLR). A Comparison of the results indicated that the MLP and RBNN performed better than the MLR model.

ANN has been used in the European rivers to establish relationship between water quality and the presence (or absence) of fish species. The results showed that the presence or absence of fish species can be used as strong ecological indicators for water quality (Jørgensen, Costanza and Xu, 2005). Mihajlović *et al*. (2010) used ANNs to model the ecological management and sulfur dioxide (SO_2) emissions in the vicinity of a copper-smelting complex in the city of Bor, Serbia. The results indicated that ANNs could be successfully used for predictions of the SO_2 emissions according to the known technological and meteorological parameters. Ay and Kisi (2013) modelled a chemical oxygen demand (COD) concentration using different artificial intelligence methods. Two different ANN methods, i.e., MLP and RBNN, and the integrated fuzzy clustering and adaptive neuro fuzzy inference system (ANFIS-FCM) were developed to estimate COD concentrations using various combinations of daily input variables such as suspended solids (SS), discharge (Q), temperature (T) and pH. RMSE, MAE and R^2 statistics were used as comparison criteria. The results indicated that the MLP and RBNN performed slightly better than the ANFIS-FCM in modelling COD. Abyaneh (2014) used multivariate linear regression (MLR) and ANN to predict BOD and COD at a wastewater treatment plant. The performance of the ANN model was evaluated using the coefficient of correlation (r), RMSE, and bias values. The computed values of BOD and COD by ANN and the regression analysis were in close agreement with their respective measured values. The results also showed that the ANN performance model was better than the MLR model.

Heydari *et al*. (2013) developed an NN technique for predicting water quality parameters in the Delaware River in Pennsylvania, USA. ANN was used to derive and develop models for predicting monthly DO values and specific conductance (SC) of a river at some selected stations. The performance of the model was evaluated by statistical criteria such as the correlation coefficient (r), RMSE and MAE. The correlation coefficients of the model for predicting the DO and SC were 0.980 and 0.989 respectively. Brosse *et al*. (1999) used ANN to assess fish abundance and spatial occupancy in the littoral zone of Lake Pareloup in the southwest of France. The study described a comparison of the ability of MLR and ANN to predict the spatial abundance of fish in the reservoir. The results revealed that ANN is more suitable for predicting fish abundance on the population scale than MLR. Moatar, Fessant and Poire (1999) modelled the pH of the Middle Loire river in France using ANNs. The river's discharges and solar radiation were used as input variables to the model. The measured values of pH were compared with the values estimated by the model using statistical tests to verify its homogeneity. The results revealed that the river pH was affected by numerous processes: biological, physical and geochemical. The model also proved satisfactory on pH simulations with a degree of accuracy on the order of 86%.

Merdun and Çinar (2010) used ANN and regression techniques in modeling the surface water quality of the Saginaw Bay watershed, Michigan, USA. The performances of hierarchical models of both techniques were evaluated using two statistical parameters, i.e., RMSE and R^2. The results showed that both ANN and MLR techniques are capable of simulating chlorophyll a (Chl-a). Radojevic *et al*. (2013) applied a feed-forward neural network (FNN) for predicting the facultative oligotrophic bacteria in two reservoirs in the central part of Serbia with different trophic states. The results of the FNN models were compared with the measured data on the basis of MAE and MSE. A comparison of the modelled values with the experimental data indicated that the model provided accurate results. Rak (2013) modelled the turbidity of water during water treatment processes at the Sosnówka reservoir in Poland using ANN. The results proved that ANN can be applied to predict the quality factors for water pre-treated in a specific technical system.

Ahangar, Soltani and Abdolmaleki (2013) predicted the concentration of manganese (Mn) in Chahnimeh reservoir in Iran using ANN. The results showed that a network with 10 hidden neurons was highly accurate in predicting the Mn concentration. Areerachakul, Sophatsathit and Lursinsap (2013) studied the integration of unsupervised and supervised NNs to predict the DO concentration in the canals of Bangkok, Thailand. The results revealed that the comparisons between the proposed technique and other techniques using the correlation coefficient (r), MAE and MSE showed that the proposed approach with a sub-space clustering technique yielded a higher degree of accuracy than other approaches without the sub-space clustering technique.

Możejko and Gniot (2008) applied an NN model for the prediction of the total phosphorus concentration in Odra River, Poland. Two models were proposed to prove the satisfactory forecasting of phosphorus concentrations: a simpler one with a single input variable and a more complex one with 14 input variables. Both ANN models showed a high ability to predict from the new data set. Lae, Lek and Moreau (1999) predicted the fish yield of African lakes using an ANN model. The results revealed that the fish yields estimated with this method were significantly related to the observed fish yields with a correlation coefficient of 0.83 ($p < 0.01$). Abdolmaleki, Ahangar and Soltani (2013) used an ANN model for predicting the Copper (Cu) concentration in the drinking water of Chahnimeh1 reservoir in Sistan-Balochistan, Iran. The results revealed that the ANN output values were very close to the actual Cu concentration, which indicated that the predicted values were accurate. Rankovi´c *et al*. (2010) used FNN model to predict the DO in the Gruˇza reservoir in Serbia. The results of the model were compared with the measured data on the basis of correlation coefficient (r), MAE and MSE. Comparing the modelled values with the experimental data indicated that the model provided accurate results.

Vicente *et al*. (2012) predicted water quality parameters in the Monte Novo reservoir, Portugal, using ANN. The results revealed that there was a good match between the observed and predicted values with the R^2 values between 0.995 to 0.998 for the training set and 0.994 to 0.996 for the test set. Neto *et al*. (2014) estimated physico-chemical parameters and metal concentrations in hydroelectric reservoirs using ANN and remote sensing images in the Amazon region, Brazil. The results revealed that the ANN reproduced the measured parameters satisfactorily. Baskaran, Nagan and Rajamohan (2010) modelled the inflow and sediment yield for Vaigai reservoir, India, using ANN. The results revealed that the observed inflow and sediment values were close to the measured values. Jeong, Kim and Joo (2006) used an ANN model to predict phytoplankton proliferations in Nakdong river, South Korea. The results revealed that the model produced a high degree of accuracy in predicting both the magnitude and timing of algal proliferations. Dedecker *et al*. (2004) used an ANN model to predict macroinvertebrates in the Zwalm river basin, Flanders, Belgium. The results indicated that the number of times a taxon was found in the whole river basin influenced the performance and the architecture of the network. Sivri *et al*. (2009) estimated the stream temperature in Degirmendere River, Turkey, using an ANN model. The results showed that the model can be utilized in the timely prediction of the temperatures of stream waters.

This present study was carried out at four locations selected on the upstream and downstream sides of the Kainji hydropower station. A map of Nigeria shows the study area (Fig. 1), while a Google image indicates the sampling locations selected (Fig. 2). The sampling locations and their corresponding coordinates are in Table 1.

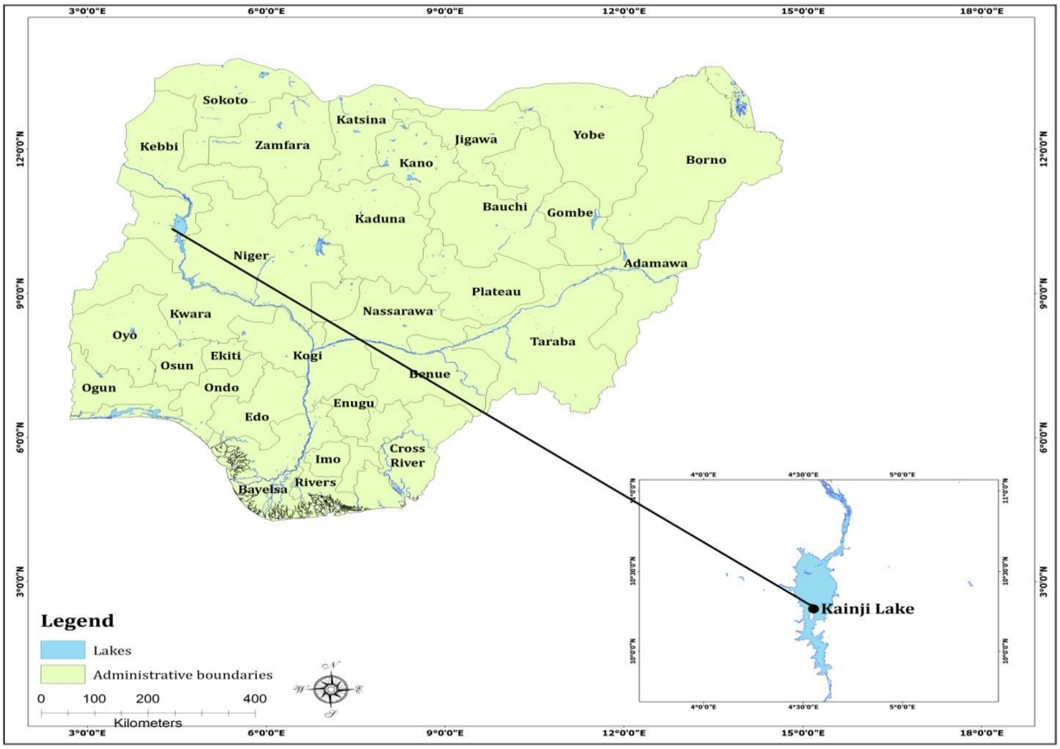

Figure 1: Map of Nigeria showing Kainji lake

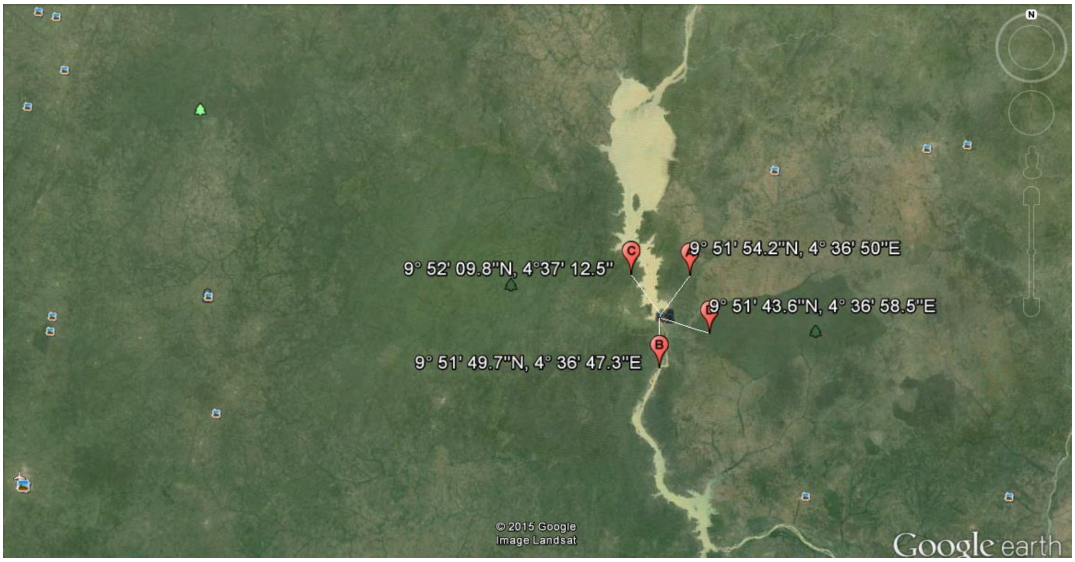

Figure 2: Google image of the selected sampling locations

Table 1: Sampling locations and coordinates

Sampling Location	*Description*	*Latitude*	*Longitude*
A	Power Intake	4° 36' 50.0"	9° 51' 54.2"
B	Tailrace	4° 36' 47.3"	9° 51' 49.7"
C	Boatyard	4°37' 12.5"	9° 52' 09.8"
D	Downstream Tailrace	4° 36' 58.5"	9° 51' 43.6"

2.0 Methodology

The data set used in this study was collected from the Environmental Section of the Kainji hydropower station, Nigeria. The monthly data was available for a period of six years (2010 to 2015). Water quality data at some important locations on the upstream and downstream sides of the Kainji hydropower reservoir were available for the power intake, boatyard, turbine discharge and tailrace. The approach used in Rankovi´c *et al.* (2010) was adopted in this study. The parameters used as the model input were: pH, Temperature, Fe^{2+}, Cl^{-}, PO_4^{3-}, NO_3^{-} and EC, while the model output was DO. ANN software in the Statistical Package for Social Sciences (SPSS) was used. MLPNN and RBFNN were used to model the DO concentration at the locations. The performance evaluation of the model was carried out using the correlation coefficient (r), MSE and MRE as presented in Equations 1, 2 and 3 (Giri and Singh, 2014). Analysis of Variance (ANOVA) was used to test if there are significant difference in the observed and modelled DO at all the locations. Also, multiple regression analysis was used to model the DO at the selected locations using the same input variables as used for the ANN models.

$$r = \frac{\sum\left(y_{pi} - \bar{y}_{pi}\right)\left(y_{oi} - \bar{y}_{oi}\right)}{\sqrt{\left(y_{pi} - \bar{y}_{pi}\right)^2 \left(y_{oi} - \bar{y}_{oi}\right)^2}} \quad (1)$$

$$MSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(y_{pi} - y_{oi}\right)^2\right]^{\frac{1}{2}} \quad (2)$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{pi} - y_{oi}}{y_{oi}}\right| \quad (3)$$

where:

y_{pi} = predicted DO

y_{oi} = observed DO

$\bar{y}_{pi}$ = mean predicted DO

$\bar{y}_{oi}$ = mean observed DO

n = total number of observations

$\sum$ = summation

3.0 Results and Discussion

The actual and modeling results for the DO at the selected locations are presented in (Figures 3 to 6). Summary of the results of the performance evaluation of the NNs for the selected locations are presented in Tables 2 to 5. ANOVA results for the observed and modelled DO at the selected sampling locations are shown in Tables 6 to 9. Multiple regression model statistics for the selected sampling locations is presented in Table 10. Typical NN architecture generated from the SPSS software for both the MLPNN and RBFNN models are presented in Figs. 7 and 8.

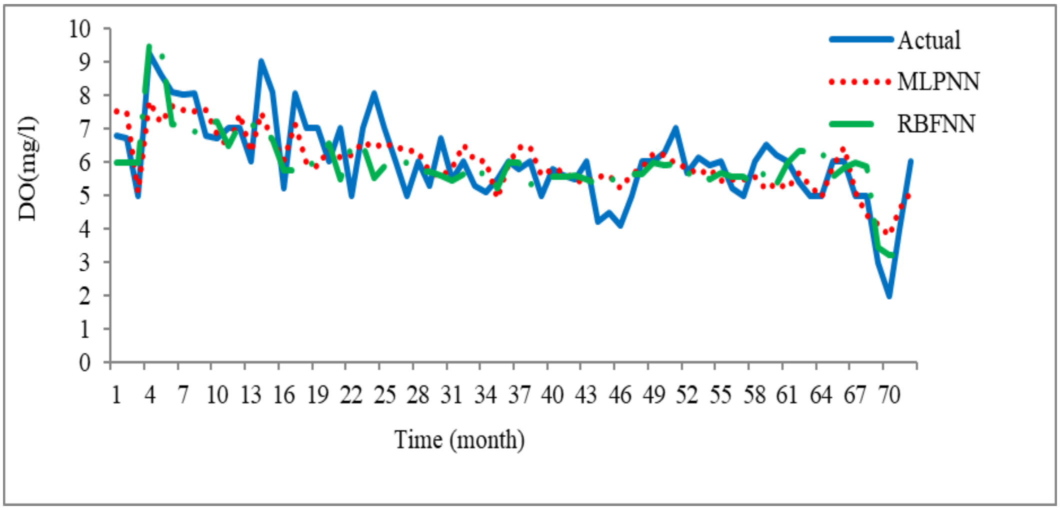

Figure 3: Actual and modelled DO (mg/l) in water at power intake

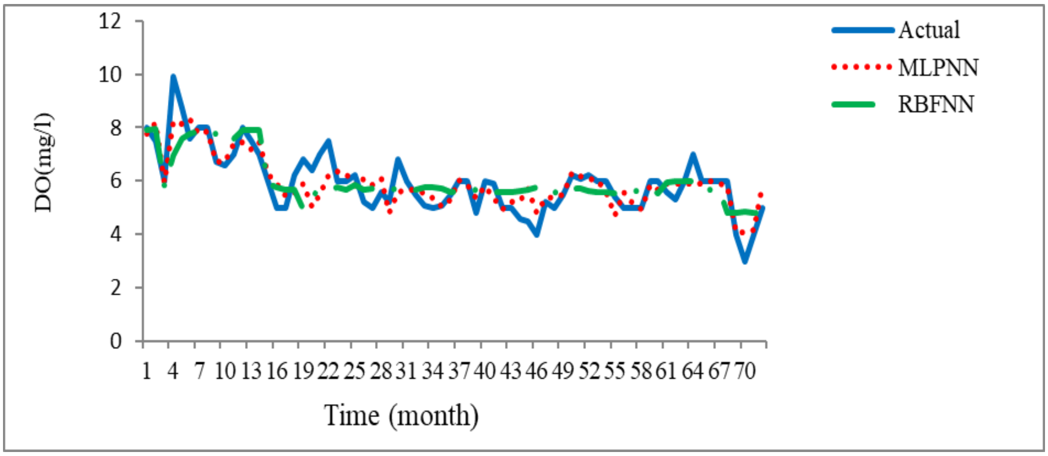

Figure 4: Actual and modelled DO (mg/l) in water at boatyard

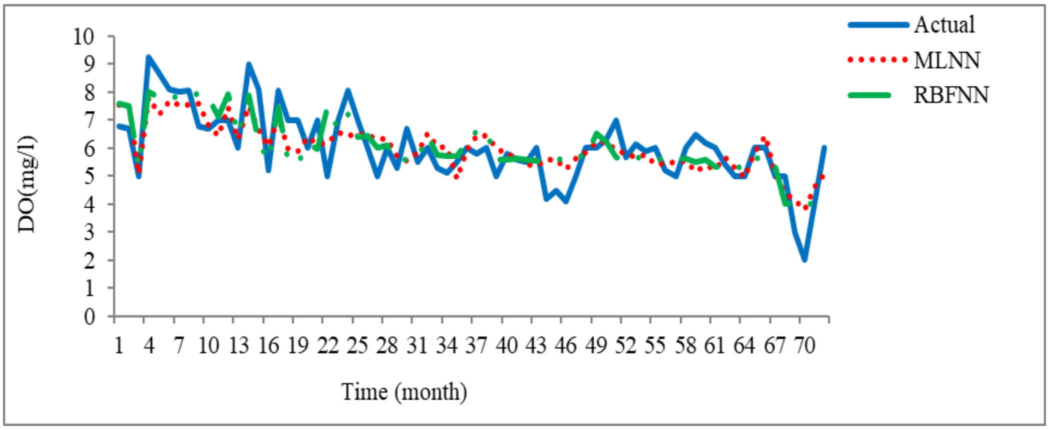

Figure 5: Actual and modelled DO (mg/l) in water at tailrace

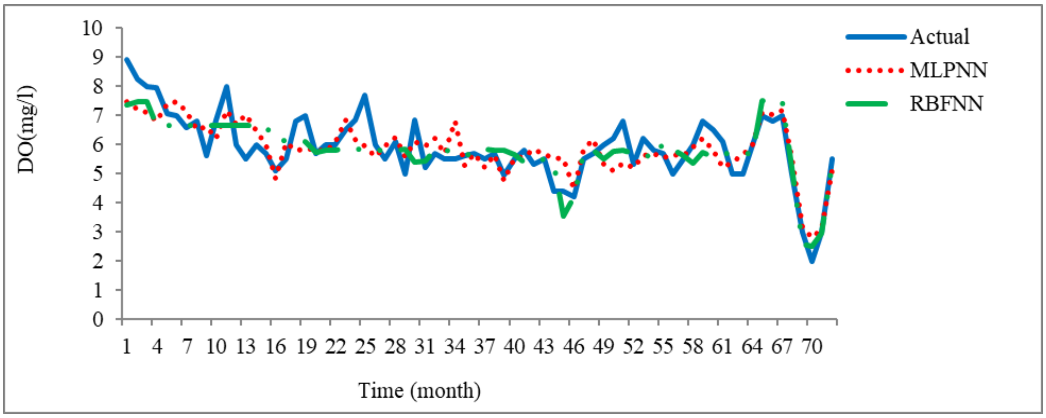

Figure 6: Actual and modelled DO (mg/l) in water at turbine discharge

Table 2: ANN model summary for DO at power intake

		MLPNN			*RBFNN*		
Sample	*Percentage (%)*	*MSE*	*MRE*	*r*	*MSE*	*MRE*	*r*
Training	77.8	3.04972	0.3382	0.61	3.96386	0.6285	0.82
Validation	22.2	1.89336	0.5232		1.946	0.792	
Total	100						

Table 3: ANN model results for DO at boatyard

		MLPNN			*RBFNN*		
Sample	*Percentage (%)*	*MSE*	*MRE*	*r*	*MSE*	*MRE*	*r*
Training	70.8	2.700	0.292	0.86	3.269	0.389	0.72
Validation	29.2	1.382	0.348		2.461	0.655	
Total	100						

Table 4: ANN model results for DO at tailrace

		MLPNN			*RBFNN*		
Sample	*Percentage (%)*	*MSE*	*MRE*	*r*	*MSE*	*MRE*	*r*
Training	70.8	2.544	0.259	0.79	3.678	0.492	0.74
Testing	29.2	2.484	0.687		2.184	1.101	
Total	100						

Table 5: ANN Model results for DO at turbine discharge

		MLPNN			*RBFNN*		
Sample	*Percentage (%)*	*MSE*	*MRE*	*r*	*MSE*	*MRE*	*r*
Training	77.8	3.255	0.385	0.80	3.434	0.454	0.81
Validation	22.2	1.909	0.413		2.135	0.513	
Total	100						

Table 6: ANOVA results for the observed and modelled DO at power intake

		Sum of squares	*df*	*Mean square*	*F*	*Sig.*
MLPNN	Between groups	39.7647	29	1.3712	4.6065	4.08E-06
	Within groups	12.5019	42	0.2977		
	Total	52.2666	71			
RBFNN	Between groups	56.8619	29	1.9608	5.0979	1.06E-06
	Within groups	16.1542	42	0.3846		
	Total	73.0161	71			

Table 7: ANOVA results for the observed and modelled DO at boatyard

		Sum of squares	*df*	*Mean square*	*F*	*Sig.*
MLPNN	Between groups	55.8165	27	2.0673	10.5401	1.009E-11
	Within groups	8.6299	44	0.1961		
	Total	64.4464	71			
RBFNN	Between groups	45.5042	27	1.6853	7.7851	1.655E-09
	Within rroups	9.5252	44	0.2165		
	Total	55.0294	71			

Table 8: ANOVA results for the observed and modelled DO at tailrace

		Sum of squares	*df*	*Mean square*	*F*	*Sig.*
MLPNN	Between groups	39.3078	29	1.3554	4.4445	6.46E-06
	Within groups	12.8088	42	0.305		
	Total	52.1165	71			
RBFNN	Between groups	50.024	29	1.7245	3.153	0.0004
	Within groups	22.9776	42	0.5471		
	Total	73.0016	71			

Table 9: ANOVA results for the observed and modelled DO at turbine discharge

		Sum of squares	*df*	*Mean square*	*F*	*Sig.*
MLPNN	Between groups	48.0606	27	1.78	7.33034	4.34E-09
	Within groups	10.68444	44	0.2428		
	Total	58.7451	71			
RBFNN	Between groups	54.2025	27	2.0075	8.313	5.68E-10
	Within groups	10.6255	44	0.2415		
	Total	64.828	71			

Table 10: Multiple regression model statistics for the locations

S/No	*Location*	*Correlation coefficient (r)*	*Standard error*
1	Power intake	0.72	0.9037
2	Boatyard	0.78	0.768
3	Tailrace	0.61	0.9555
4	Turbine discharge	0.77	0.8552

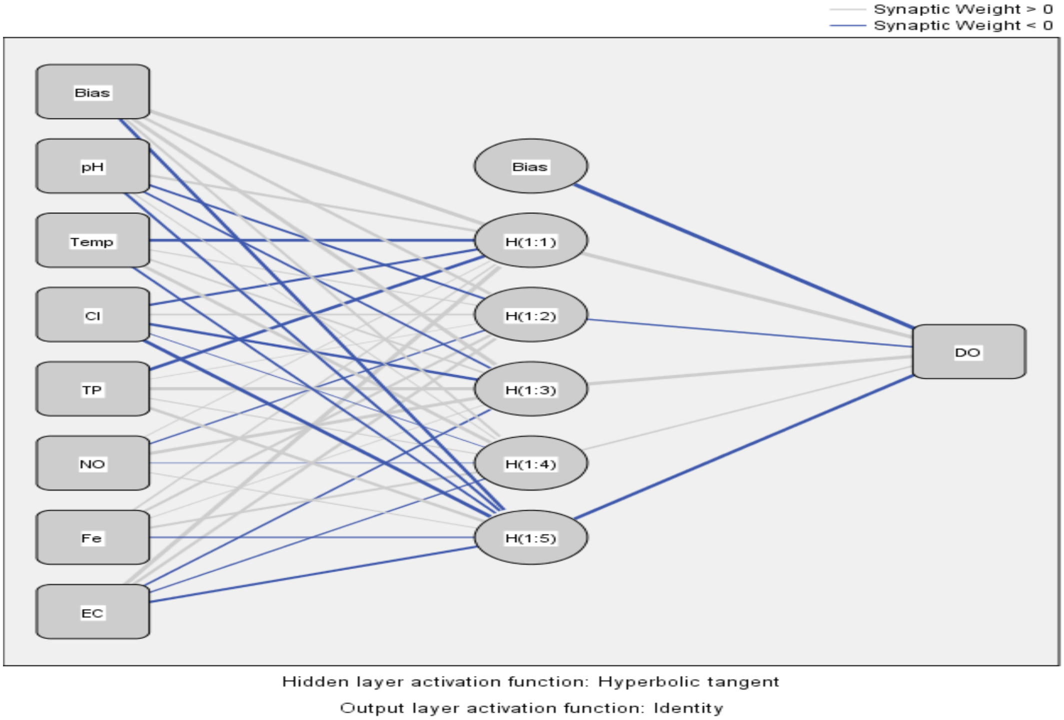

Figure 7: Typical MLPNN model architecture for DO

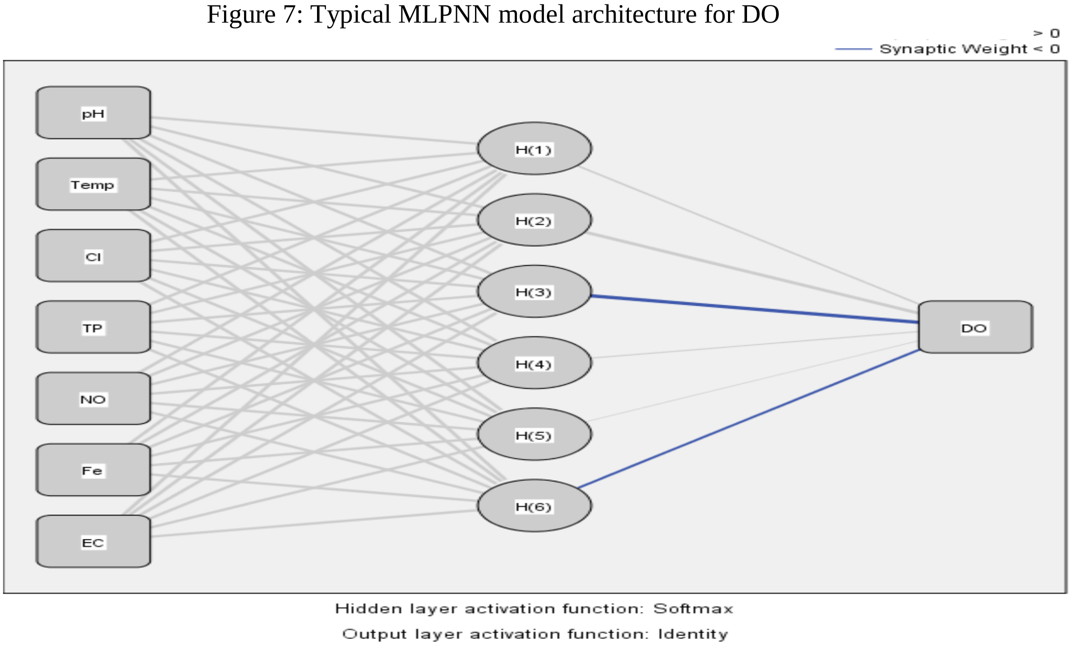

Figure 8: Typical RBFNN model architecture for DO

The percentages of data used in the model calibration/training and validation/testing were over 70% and 20% respectively for all the locations. The correlation coefficients (r) of 0.605, 0.859, 0.803 and 0.789 for the power intake, boatyard, turbine discharge and tailrace location respectively, revealing strong and positive relationships between the actual and simulated DO concentrations at all the locations. The values of MSE for training and testing at the power intake location were 9.3008 and 3.5848 using the MLPNN approach, while that of RBFNN were 15.7122 and 3.7881 respectively. Also, the values of MRE for training and testing were 0.3382 and 0.5232 using MLPNN, while those of the RBFNN were 0.6285 and 0.792 respectively at the power intake station. The MSE for the training and testing using the two NNs approaches at the boatyard location varied between 1.9106 and 10.6872, while the MRE for training and testing ranged between 0.2918 and 0.6554. The MSE for the training and testing using the two NN approaches at the turbine discharge location varied between 3.6477 and 11.7945, while the MRE for training and testing varied between 0.3853 and 0.51256.

The MSE for the training and testing using the two NN approaches at the tailrace ranged between 4.769 and 13.5259, while the MRE ranged between 0.2588 and 1.1013. The results of this study are comparable with those obtained in earlier studies such as (Giri and Singh, 2014; Rankovi´c *et al.*, 2010). ANOVA results revealed that there were no statistically significant differences in the actual and modelled DO using the two ANN modeling approaches at the locations. This implies that the ANN models simulated the observed DO concentration in water perfectly. Results of the multiple regression model statistics for the DO at all the selected locations indicated that the correlation coefficient varied between 0.61 to 0.77.

4.0 Conclusion

Modeling water quality variables is a very important aspect in the analysis of any aquatic systems. The chemical, physical and biological components of aquatic ecosystems are very complex and nonlinear. In recent years, computational-intelligence techniques such as neural networks, fuzzy logic and combined neuro-fuzzy systems have become very effective tools for the identification and modeling of nonlinear systems. In this paper, MLPNN and RBFNN models were developed to simulate the concentration of DO at the Kainji hydropower reservoir in Nigeria. ANN structure was designed and trained using the neural network toolbox in SPSS. The performance of the ANN was tested using the correlation coefficient, MRE and MSE. The results of the simulation showed that the application of the NNs for the prediction of DO gives satisfactory results for all the selected locations using the two NN modeling approaches. It can be concluded that NN modeling tools and multiple regression analysis are very efficient and useful alternative for the computation of water quality parameters and can therefore be adopted to model various parameters in rivers, lakes and streams in Nigeria.

5.0 Acknowledgements

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