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MODELLING HEAVY METAL CONCENTRATION IN KAINJI HYDROPOWER RESERVOIR, NIGERIA

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ABSTRACT The primary function of impounding water at the Kainji Dam is to generate hydropower, while it also offers opportunities for development of fishery, irrigation, recreation and navigation. The operation of the Kainji dam reservoir in Nigeria over the years has concentrated solely on power generation with little or no cognizance given to environmental aspect. The objectives of the study were to model concentration of selected heavy metals in sediment of the reservoir using Multilayer Perceptron Neural Network (MLPNN) and Radial Basis Function Neural Network (RBFNN) were used to model sediment quality parameters at selected location in the reservoir. The results showed that the application of the NN approaches to model the sediment quality parameters gives good outcomes for all the selected locations with strong correlation coefficient of at least 0.72. Also the Root Mean Square Error (RMSE) and Mean relative Error (MRE) are found within acceptable limits. Concentrations of Cu²⁺, Pb²⁺ and Cr³⁺ in sediment vary between 27.9 to 68.6 mg/kg, 21.9 to 35.0 mg/kg and 39.7 to 95 mg/kg respectively. These fell within the tolerance limits of 80, 35 and 95 mg/kg stipulated by Washington Department of Ecology Sediment Quality Guidelines (WDOESQG) for concentration of heavy metals in sediment. The modelling approaches can be adopted in similar studies.

1. Introduction

Reservoirs play an important role in the livelihood of the humans in Africa and worldwide. They contribute to water supply, irrigation, hydropower generation, fishery development and flood control. They are also tourist attraction and set up new areas for development. However, contamination of aquatic ecosystems in reservoirs with a wide range of pollutants has been always a matter of concern. Reservoirs have been subjected to various forms of degradation due to pollution arising from domestic wastes, industrial effluent, agricultural run offs and bad fishing practices (Nzeve *et al.*, 2014). A good sediment quality is crucial to maintain a healthy aquatic ecosystem, which ensures good protection of human health and aquatic life (Nzeve *et al.*, 2014). Heavy metals have high risk impacts due to their toxicity, abundance, persistence and bio-accumulation in sediment. Identification of contamination level and ecological risks associated with heavy metal pollution of sediments in specific case study in Bulgaria was done on the base of index analyses approach (Todorova *et al.*, 2016).

Lopez *et al.* (2006) studied elemental ratios in sediments as indicators of ecological processes in Spanish reservoirs. Sediment data were obtained from Catalonian and Lozoya reservoirs. A preliminary study of the limnological significance of the major elemental composition and ratios in sediments were analysed and two data-sets from different limnological regions were obtained. Reservoirs from eastern and western Spain presented significant differences in the chemical composition of their sediments: higher average values for calcium and magnesium appear in the eastern reservoirs, while, in western Spain, higher mean values were found for alumino-silicate elements (i.e. silicon (Si), aluminium (Al) and potassium (K), iron and phosphorus. Ca/Al ratio appears related to water mineralization and in the eastern region, the slope of the regression line between Ca/Al and conductivity reflected catchment mineralogy. In superficial sediments from both eastern and western regions, Fe/Al was linked to the authigenic precipitation of iron oxides and appears closely related to sedimentary phosphorus accumulation above background levels.

2. Methodology

Sediment quality data such as Chromium (Cr^{3+}), Lead (Pb^{2+}) and Copper (Cu^{2+}) were collected from the Environmental unit of Kainji hydropower station (EUKHS, 2015). The monthly sediment quality data was available for power intake, boatyard, turbine discharge and tailrace locations for a period of six years (2008-2013). Figure 1 is the map of Nigeria showing Kainji Lake while Figure 2 is the Google imagery of Kainji reservoir showing the location of water quality sampling.

MLPNN and RBFNN modelling approaches were used in this study due to their applications in modelling linear and non-linear events. Concentration of heavy metals: Cu^{2+} , Pb^{2+} and Cr^{3+} in the reservoir sediment were modelled using ANN approaches as explained in (El Badaoui *et al.*, 2013). Physico-chemical variables like: pH, PO_4^{3-} , Ca^{2+} , Mg^{2+} , K^+ , Na^+ and TSS were used as model inputs while the output were Cu^{2+} , Pb^{2+} and Cr^{3+} . ANN software tool box in the SPSS 16.0 version was applied to model the heavy metals in the reservoir sediment at the selected locations. The performance evaluation of the model was carried out using the correlation coefficient (r), root mean square error (RMSE) and mean relative error (MRE) as shown in Equations (1) to (3) respectively (Giri and Singh, 2014).

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

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

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

where:

y_{pi} = predicted parameter

y_{oi} = observed parameter

\bar{y}_{pi} = mean predicted parameter

\bar{y}_{oi} = mean observed parameter

n = total number of observations

Figure 1 Map of Kainji lake with Nigeria inset

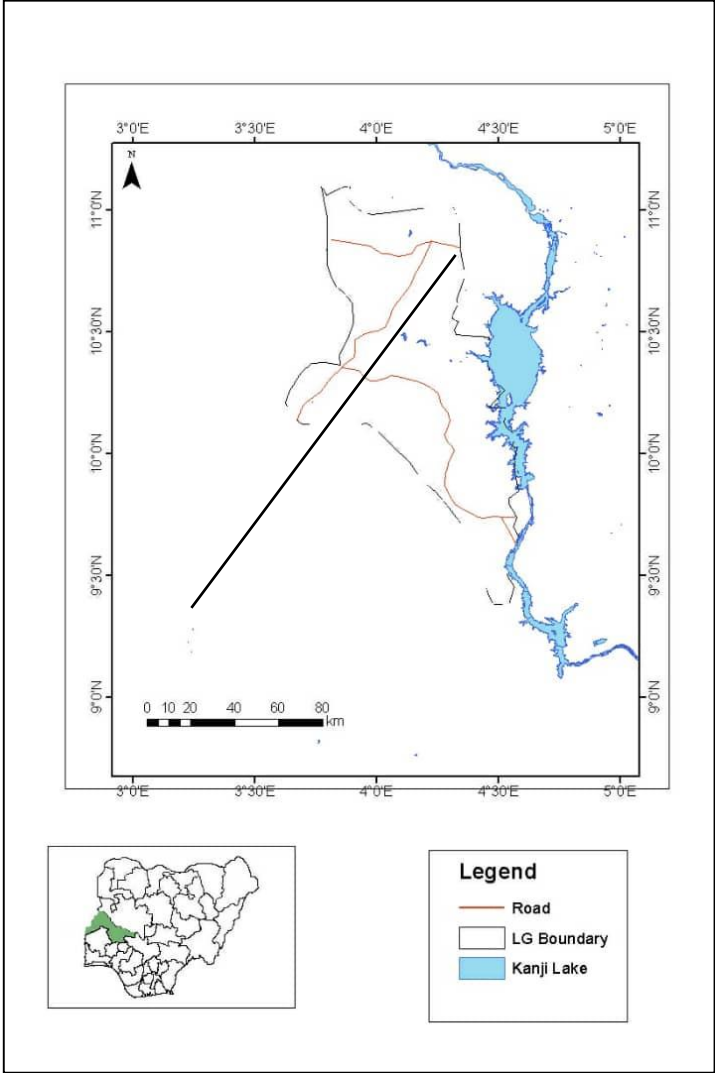
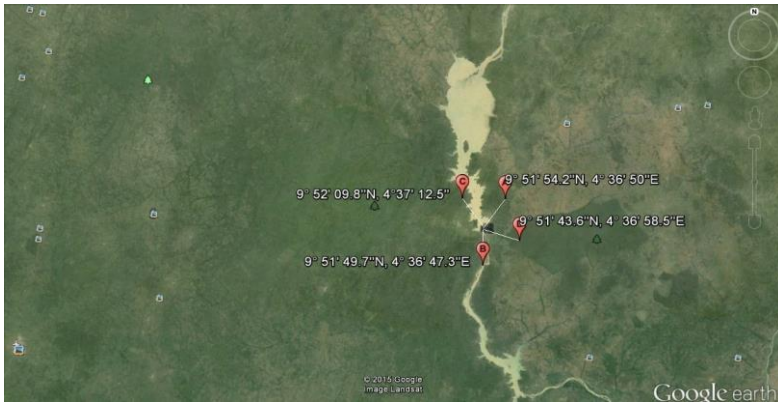


Figure 2 Google imagery of Kainji reservoir showing sampling locations



3. Results and discussion

Actual and modelled results for the Cu^{2+} , Pb^{2+} and Cr^{3+} concentrations in sediment at the selected locations at the station are presented in Figures 3 to 14. Results of the performance evaluation of the two neural network (NN) approaches for the concentration of selected heavy metals in sediment at different locations are shown in Tables 1-12.

Figure 3 Actual and modelled Cu^{2+} in sediment at power intake for Tailrace

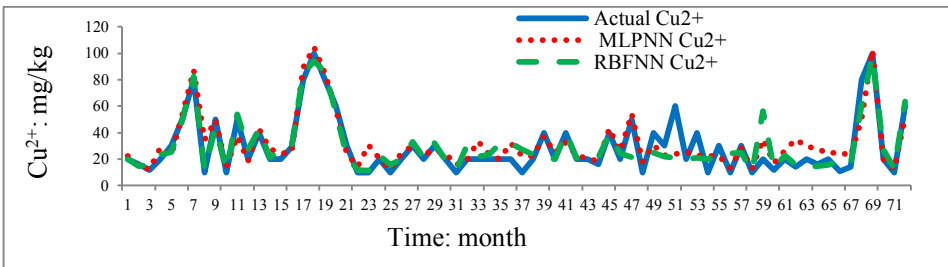


Figure 4 Actual and modelled Cu^{2+} in sediment at boatyard for Tailrace

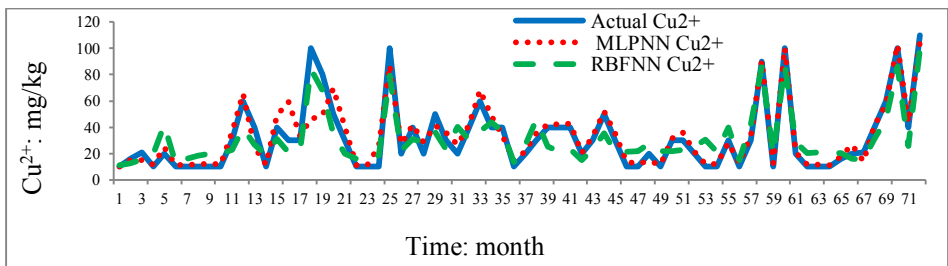


Figure 5 Actual and modelled Cu²⁺ in sediment at tailrace for Tailrace

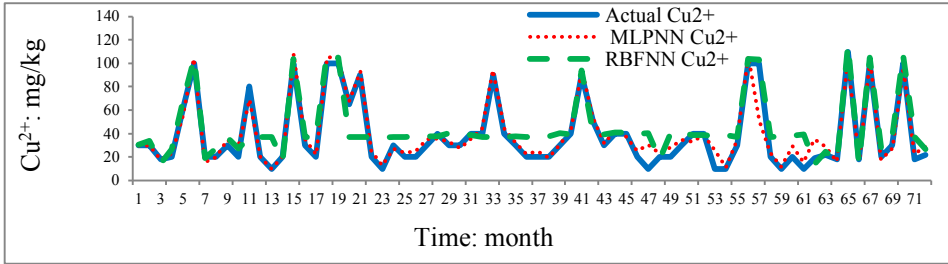


Figure 6 Actual and modelled Cu²⁺ in sediment at turbine discharge for Tailrace

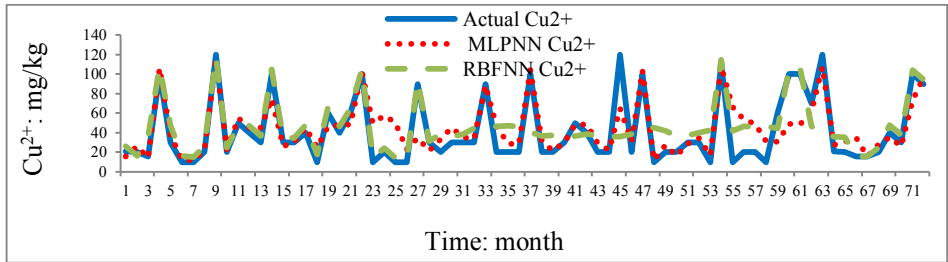


Table 1 ANN model results for Cu²⁺ in sediment at power intake

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.491	0.807	0.90	4.155	0.691	0.89
Validation	22.2	1.828	0.806		2.063	1.027	
Total	100						

Table 2 ANN model results for Cu²⁺ in sediment at boatyard

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.366	0.763	0.92	4.905	0.875	0.86
Validation	22.2	2.208	0.892		2.311	0.910	
Total	100						

Table 3 ANN model results for Cu^{2+} in sediment at tailrace

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.489	0.806	0.96	5.236	0.997	0.85
Validation	22.2	2.208	0.865		2.930	1.044	
Total	100						

Table 4 ANN model results for Cu^{2+} in sediment at turbine discharge

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.226	0.714	0.82	5.194	0.981	0.76
Validation	22.2	4.511	0.951		2.520	1.028	
Total	100						

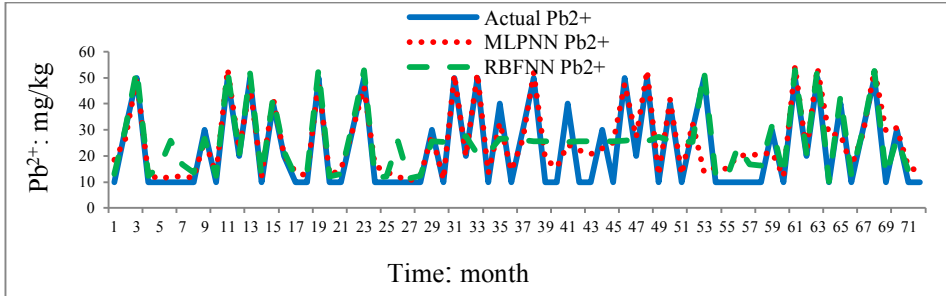
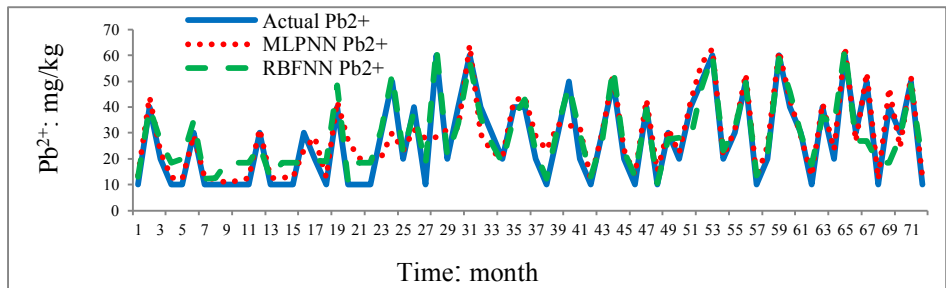
Figure 7 Actual and modelled Pb^{2+} in sediment at power intake for TailraceFigure 8 Actual and modelled Pb^{2+} in sediment at boatyard for Tailrace

Figure 9 Actual and modelled Pb²⁺ in sediment at tailrace for Tailrace

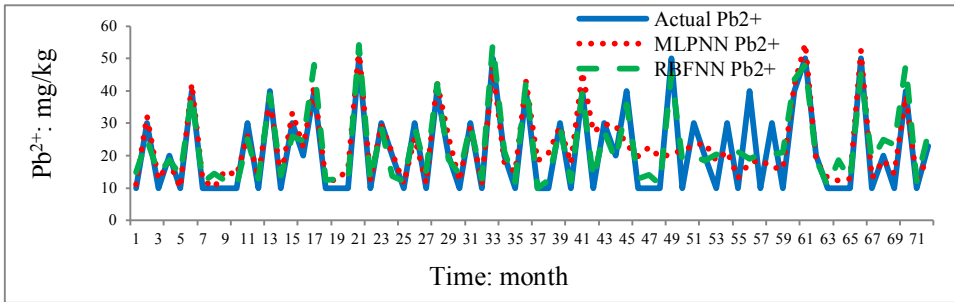


Figure 10 Actual and modelled Pb²⁺ in sediment at turbine discharge for Tailrace

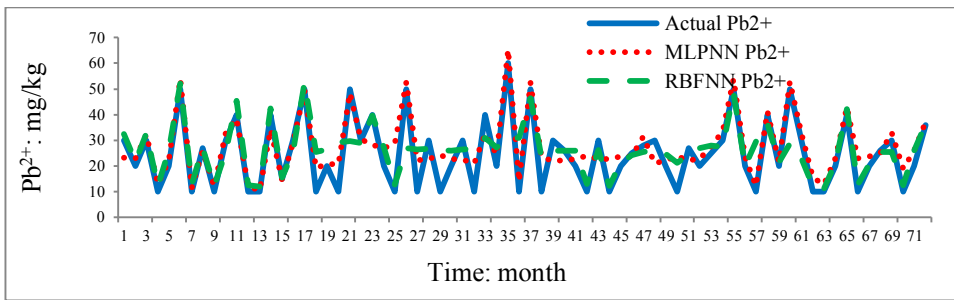


Table 5 ANN model results for Pb²⁺ in sediment at power intake

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.804	0.923	0.89	4.692	0.881	0.78
Validation	22.2	2.893	0.974		3.000	1.046	
Total	100						

Table 6 ANN model results for Pb²⁺ in sediment at boatyard

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.741	0.899	0.89	4.602	0.770	0.92
Validation	22.2	2.372	0.974		3.570	0.994	
Total	100						

Table 7 ANN model results for Pb^{2+} in sediment at tailrace

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	5.153	1.062	0.85	4.922	0.969	0.91
Validation	22.2	3.337	0.946		3.550	1.069	
Total	100						

Table 8 ANN model results for Pb^{2+} in sediment at turbine discharge

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.763	0.907	0.89	5.130	0.957	0.75
Validation	22.2	2.365	0.788		2.540	1.244	
Total	100						

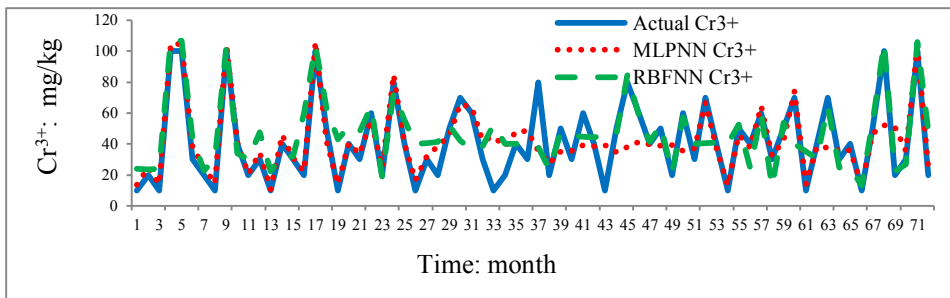
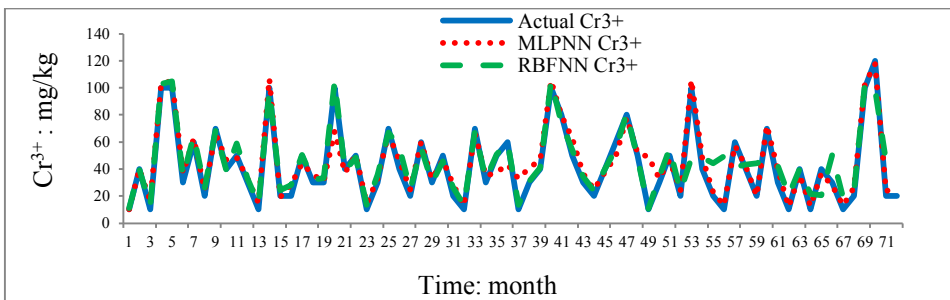
Figure 11 Actual and modelled Cr^{3+} in sediment at power intake for TailraceFigure 12 Actual and modelled Cr^{3+} in sediment at boatyard for Tailrace

Figure 13 Actual and modelled Cr³⁺ in sediment at tailrace for Tailrace

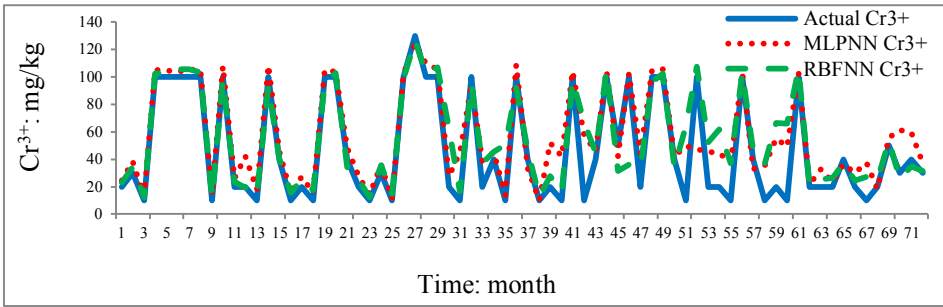


Figure 14 Actual and modelled Cr³⁺ in sediment at turbine discharge for Tailrace

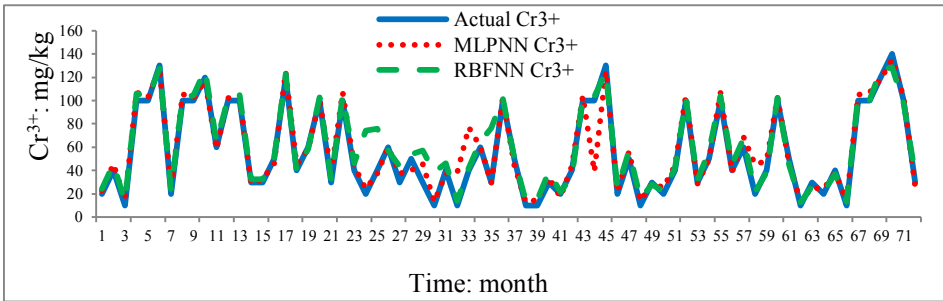


Table 9 ANN model results for Cr³⁺ in sediment at power intake

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.987	0.907	0.84	4.462	0.724	0.8
Validation	22.2	2.878	0.921		2.490	0.925	
Total	100						

Table 10 ANN model results for Cr³⁺ in sediment at boatyard

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.220	0.712	0.96	4.676	0.795	0.91
Validation	22.2	1.957	0.921		2.300	1.019	
Total	100						

Table 11 ANN model results for Cr^{3+} in sediment at tailrace

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	5.238	1.098	0.93	4.835	0.850	0.89
Validation	22.2	2.915	0.998		3.024	1.026	
Total	100						

Table 12 ANN model results for Cr^{3+} in sediment at turbine discharge

Sample	Percentage (%)	MLPNN			RBFNN		
		RMSE	MRE	r	RMSE	MRE	r
Training	77.8	4.768	0.910	0.96	4.780	0.831	0.96
Validation	22.2	3.028	0.822		2.628	1.501	
Total	100						

4. Discussion of results

The plots of the actual and modelled Cu^{2+} at the sampling locations presented in Figures 3 to 6 indicated strong relationship between the actual and modelled Cu^{2+} concentration at the locations. The correlation coefficients (r) of Cu^{2+} concentration in sediment using MLPNN were: 0.90, 0.92, 0.96 and 0.82 for power intake, boatyard, tailrace and turbine discharge locations respectively while r for RBFNN approach 0.72, 0.89, 0.86 and 0.85 respectively (Tables 1-4). The values of RMSE for training and validation at the power intake location range between 1.828 to 4.491, while the MRE for both training and validation at the power intake location varies between 0.691 and 1.027 (Table 1). Also the RMSE for training and validation were found between 2.208 and 4.905 while that of the MRE were observed to be within 0.763 and 0.910 at the boatyard station. The RMSE for the training and at the tailrace location varied between 2.208 and 5.236 (Table 2) while the MRE for training and validation ranged between 0.806 and 1.044 (Table 3). The RMSE for the training and validation at the turbine discharge location varied between 2.52 and 5.1939 while the MRE for training and validation ranged between 0.7144 and 1.0276 (Table 4).

The plots of the actual and simulated Pb^{2+} at the sampling locations presented in Figures 7-10 revealed a strong relationship between the actual and simulated Pb^{2+} concentrations in sediment at the locations. The correlation coefficients (r) of Pb^{2+} concentration in sediment using MLPNN were: 0.89, 0.89, 0.85 and 0.89 for power intake, boatyard, tailrace and turbine discharge locations respectively while r for RBFNN were found to be 0.78, 0.92, 0.91 and 0.75 respectively (Tables 5-8). The values of RMSE for training and validation at the muscle intake location using the two NN approaches varied

between 2.893 to 4.804, while the MRE for both training and validation at the power intake location ranged between 0.881 and 1.046 (Table 5). Also the RMSE for training and validation were found between 2.372 and 4.741 while that of the MRE were observed to be within 0.770 and 0.994 at the boatyard station (Table 6). The RMSE for the training and testing at the tailrace location varied between 3.337 and 5.153 while the MRE for training and validation ranged between 0.946 and 1.069 (Table 7). The RMSE for the training and validation at the turbine discharge location ranged between 2.365 and 5.130 while the MRE for training and validation ranged between 0.788 and 1.244 (Table 8).

The plots of the actual and simulated Cr^{3+} at the sampling locations presented in Figures 11-14 also revealed a strong relationship between the actual and simulated Cr^{3+} concentrations in sediment at the locations. The correlation coefficients (r) of Cr^{3+} concentration in sediment using MLPNN were: 0.84, 0.96, 0.93 and 0.96 for power intake, boatyard, tailrace and turbine discharge locations respectively while r for RBFNN were found to be 0.80, 0.91, 0.89 and 0.96 respectively (Tables 9-12). The values of RMSE for training and validation at the power intake varied between 2.490 to 4.987, while the MRE for both training and validation at the power intake location ranged between 0.724 and 0.925 (Table 9). Also the RMSE for training and validation using the two NN approaches were found between 1.957 and 4.676 while that of the MRE were observed to be within 0.7124 and 1.019 at the boatyard station (Table 10). The RMSE for the training and validation at the tailrace location varied between 2.915 and 5.238 while the MRE for training and validation ranged between 0.850 and 1.098 (Table 11). The RMSE for the training and validation at the turbine discharge location ranged between 2.628 and 4.780 while the MRE for training and validation ranged between 0.822 and 1.501 (Table 12). The RMSE and MRE obtained for Cu^{2+} , Pb^{2+} and Cr^{3+} concentration in sediment are in the same range with the RMSE values varying between 0.33 to 23.6 and MRE values varying between 0.15 to 15.23 that were obtained in similar studies as reported by (Giri and Singh, 2014; Ay & Kisi, 2013; Rankovi'c *et al.*, 2010; Palani *et al.*, 2008; Chokananporn & Tansakul, 2008). Concentrations of Cu^{2+} , Pb^{2+} and Cr^{3+} in sediment vary between 27.9 to 68.6 mg/kg, 21.9 to 35.0 mg/kg and 39.7 to 95 mg/kg respectively. These fell within the tolerance limits of 80, 35 and 95 mg/kg stipulated by Washington Department of Ecology Sediment Quality Guidelines (WDOESQG) for concentration of heavy metals in sediment (Easthouse, 2009).

5. Conclusion

Modelling the Cu^{2+} , Pb^{2+} and Cr^{3+} concentrations in sediment at all the sampling locations around the Lake using MLPNN and RBFNN approaches revealed that the two modelling methods modelled the parameters very well. The evaluation statistics of the models using: r , MRE and RMSE showed that the application of the NN approaches to model the sediment quality parameters gives good outcomes for all the selected locations. These modelling approaches can be adopted in similar studies.

6. Acknowledgements

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References

- Ay M and Kisi O (2013) Modelling COD concentration by using different artificial intelligence methods. *Digital Proceedings of ICOEST, Cappadocia* Nevsehir, Turkey. pp. 477–489.
- Chokananporn W and Tansakul A (2008) Artificial neural network model for estimating the surface area of fresh Guava. *Asian Journal of Food and Agro-Industry* 1(3): 129–136.
- Easthouse KB (2009) Sediment Quality Assessment of Lake Rufus Woods and Chief Joseph Dam. A Technical Report Submitted to U.S. Army Corps of Engineers Seattle District, USA. pp. 1–21.
- El-Badaoui H et al. (2013) Application of the artificial neural networks of MLP type for the prediction of the levels of heavy metals in Moroccan aquatic sediments. *International Journal of Computational Engineering Research* 3(6): 75–81.
- EUKHS (2015) *Water quality parameter data collected from the environmental unit.* Kainji Hydropower Station, New Bussa, Nigeria.
- Giri A and Singh NB (2014) Comparison of Artificial Neural network algorithm for water quality prediction of river Ganga. *Environmental Research Journal* 8(2): 55–63.
- Lopez P et al. (2006) Elemental ratios in sediments as indicators of ecological processes in Spanish Reservoirs. *Limnetica* 25(1–2): 499–512.
- Nzeve JK et al. (2014) Determination of heavy metals in sediments of Masinga reservoir, Kenya. *Journal of Environment and Earth Science* 4(20): 125–132.
- Palani S et al. (2008) An ANN application for water quality forecasting. *Marine Pollution Bulletin* 56: 1586–1597.
- Rankovi'c V et al. (2010) Neural network modelling of dissolved oxygen in the Gru'za reservoir, Serbia. *Ecological Modelling* 221: 1239–1244.
- Todorova Y et al. (2016) Contamination and ecological risk assessment of long-term polluted sediments with heavy metals in small hydropower cascade. *Water Resour. Manage.* 30: 4171–4184.