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MODELLING OF TURBIDITY VARIATION IN A WATER TREATMENT PLANT

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Abstract: Runoff is one of the principal factors that determine the level of surface water turbidity. The determination of optimum coagulant dose for the turbidity removal by the traditional method, jar tests is expensive, it takes time and may not be effective in the response to the changes in raw water quality in real time. These issues can therefore be alleviated with the use of modelling. This work made use of Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models to predict treated water turbidity. Precipitation and Water Treatment Plant (WTP) data was analyzed and the treated water turbidity was predicted using. The aim was to find out which variables affect and create simple and reliable prediction models which can be used in an early warning system. Both ANN and MLR models accuracy of were compared. Results showed that it is possible to predict the baseline level of treated water turbidity in drinking water treatment plants with a simple model. Precipitation, variation in raw water turbidity, coagulant dosage and retention time are variables that mostly affect the amount of treated water turbidity. The accuracies of MLR and ANN models were found to be almost the same.
Keywords: Artificial Neural Network, Rainfall, Turbidity, Water Treatment Plant

INTRODUCTION

Water has been identified as one of the most abundant natural resources on earth, being 75% of the earth surface [1]. The need for water is universal and without water, life will simply cease to exist. Earth's water is constantly in motion, passing from one state to another and from one location to another, which makes its rational planning and management a very complex and difficult task.

Water quality standards set limits on the concentrations of impurities allowed in water. Standards also affect the selection of raw water sources and the choice of treatment processes. The development of water quality standards began in the United States in the early 20th century [2]. The contaminant of most concern is high turbidity, especially rapid increases in turbidity, due to erosion and sediment runoff. Turbidity is the measure of water clarity and transparency and it is one of the primary pollutants regulated in finished drinking water under the Safe Drinking Water Act [3].

Goransson et al. [4] investigated the influence of rainfall, surface runoff and river flow on the temporal and spatial variability of turbidity in a regulated river system. A six year time series data on precipitation, discharge and turbidity from six stations along the river were examined using linear correlation and regression analysis, combined with nonparametric tests. The results showed that there is no simple relationship between discharge, precipitation and turbidity. Możejko and Gniot [5] applied ANN for time series modeling of total phosphorous concentrations in the Odra River. Data from the monitoring site was used for training, validating and testing of the model. The result showed a high ability of the model to predict the parameter. Samira et al. [6] modelled total dissolved solid (TDS) at the Simineh River in northwest Iran using ANN. The input parameters to the model were Calcium (Ca^{2+}), Chloride (Cl^-), Magnesium (Mg^{2+}), Sodium (Na^+), Bicarbonate (HCO^{3-}), Sulfate (SO_4^{2-}) and water discharge (Q) from 1993 to 2011. The results revealed that Mg^{2+} and Ca^{2+} concentrations were the most and least influential parameters with approximate values of 18 and 12 % respectively. Leon-Luque et al. [7] developed a model of Artificial Neural Network (ANN) that, when faced with real time variations of turbidity is able to calculate an indicated dose of coagulant, with the aim of achieve effective coagulation in the trial water and avoid excessive or insufficient presence of coagulant, minimize the need to make jars test continuously and reduce economic losses due to inadequate spending of coagulant, while the input parameters are turbidity, pH, conductivity, alkalinity and temperature. Modelling of the water turbidity using some water parameter to develop useful models for the determination of turbidity was also carried out by some authors, but the work did not consider the effect of precipitation variation as one of the factors that determines the level of turbidity in surface water [8,9].

An ANN typically consists of three layers: an input layer, one or more hidden layers and an output layer. External inputs of the network are received by neurons in the input layer. Inputs are multiplied by interconnection weights and sent forward to the hidden layer where they are summed and processed by a nonlinear transfer function. The Multilayer Perceptron (MLP) and Radial Basis Function (RBF) are the commonly used neural network model. MLP and RBF are feed forward ANN which utilizes a supervised learning technique called back propagation for training a network. Neural networks are trained by examples using historical data. Back-error propagation, or back propagation, is widely and successfully used in Neural Network paradigms because it is easy to understand [7]. Performance of ANN models can be evaluated for example using Root Mean Square Error (RMSE), Mean Relative Error (MRE) and coefficient of determination (R^2). MRE can be used to determine whether model predictions are suitable for process control. R2 value can be used to compare the relative performance of the models [10].

MATERIALS AND METHODS

— The study area

Asa reservoir as shown in Figure 1 [11] is located in Ilorin, Kwara state, Nigeria. Although the water quality is still good, erosion, degradation, negative influence of toxic pollution from heavy metals and human activities at the upstream of Asa River threaten its water quality. It is located on longitude 4°35'E and latitude 8°30'N. The population of Ilorin from 2006 censes is estimated to be 781,934 [12]. Ilorin metropolis presently occupies an area of about 89 Km^2 while three main rivers that flow through the city are Oyun, Asa, and Moro [13].

— Data collection

Turbidity data, coagulant dose and retention time were obtained from Asa dam water treatment plant. The turbidity data obtained are daily turbidity data for a period of five consecutive years ranging from 2014 to 2018 for both raw and treated water. Daily coagulant dose data (mg/l) were also obtained from 2014 to 2018 and retention time at the sedimentation tanks were obtained through measurement and calculation.

Precipitation data obtained from the Nigerian Meteorological Agency (NIMET), Abuja, Nigeria which includes rainfall data from Ilorin, Ibadan, Ogbomosho and Oshogbo gauging stations for the five consecutive years ranging from 2014 to 2018. The data obtained were daily precipitation data which are measured in (mm)

DATA ANALYSIS

— Estimation of precipitation data for asa dam site

Precipitation data from Ilorin, Ibadan, Ogbomosho and Oshogbo gauging stations were used to determine the rainfall responsible for the runoff in the Asa River (Figs 2 and 3).

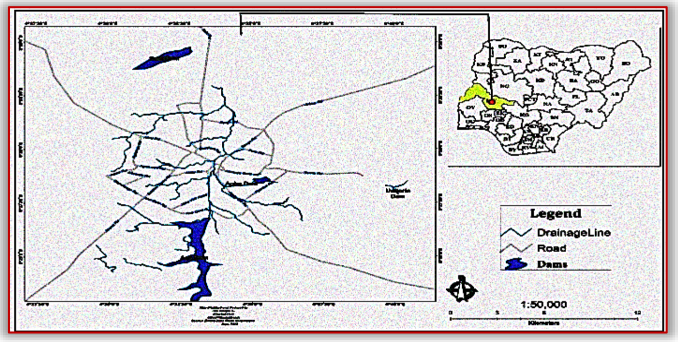

Figure 1. Map of Ilorin showing the location of the lake dams. Inset: map of Nigeria showing the states [10].

The mathematical expression for weighted average method is presented in equation (1)

$$P1 = \frac{\frac{P_2}{d2^2} + \frac{P_3}{d3^2} + \frac{P_4}{d4^2} + \frac{P_5}{d5^2}}{\frac{1}{d2^2} + \frac{1}{d3^2} + \frac{1}{d4^2} + \frac{1}{d5^2}} \qquad (1)$$

where P_1, P_2, P_3, P_4 and P_5 is the precipitation at Asa dam site, Ogbomosho, Oshogbo, Ibadan and Ilorin respectively while d_2, d_3, d_4 and d_5 is the respective distance from Ogbomosho, Oshogbo, Ibadan and Ilorin to the watershed centroid.

— Coagulant dose and retention time

The coagulant dose varies directly with turbidity of the raw water quality. The daily alum consumption between 2014 and 2018 were analysed and the monthly mean was established while the retention time in the sedimentation tank was calculated from equation 2.

$$\text{Retention time} = \frac{\text{flowrate of the intake(s)pump}}{\text{volume of the clarifier}} \qquad (2)$$

— Multiple regression models

Multiple Regression Models are statistical tool for modeling variables with one dependent and two or more independent variables. Equation (3) is a multiple regression model that can be used to assess the performance of typical water treatment plant.

$$Y = a_1 + b_1X_1 + b_2X_2 + b_2X_2 + \ldots + b_nX_n + C \qquad (3)$$

where: X_1, X_2,.....,X_n =set of independent; Y = dependent variable; a_1, b_1,...b_n = constant; c = error term (negligible). However, for this study, Y = treated water turbidity (NTU); X_1 = Coagulant dose (ml/g); X_2 = Rainfall (mm); X_3 = Retention time (t) and; X_4 = Raw water turbidity (NTU)

Two ANN modeling approaches; that is Multilayer Perceptron Neural Network (MLPNN) and Radial Basic Function Neural Network (RBFNN) in Statistical Package for Social Science (SPSS) software version 16.0 were used to model treated water turbidity at Asa dam WTP as a function of raw water turbidity, retention time, coagulant dose and precipitation. Over 80% and less than 20% of the data set were used for model training and testing. The performance evaluation of the models was carried out using RMSE, MRE and correlation coefficient (r).

RESULTS AND DISCUSSION

— Rainfall trends

It was observed that rainfall and raw water turbidity followed similar trend pattern, hence raw water turbidity varies with amount of rainfall. After treatment, it was noticed that the water turbidity reduced drastically (Figure 4). The turbidity increases from April through September and reduces as the rainfall reduces as shown in Figure 4. It was also observed that rainfall increases from 50 mm in April to above 100 mm in May and slightly decrease in June and reach the peak of 250 mm in August. It was also revealed that the variations in the rainfall trend at the observed locations are the same. The study also revealed that coagulant dosage varied with the raw water turbidity. This pattern was probably due to the amount of runoff entering the Asa dam reservoir at that time of year. The turbidity of the raw water reduces at the end of filtration and disinfection resulting in lower levels of suspended and dissolved solids washed by the run-off due to rainfall. It is evident that turbidity levels reduce considerably along the treatment process units due to settlement of flocs formed during coagulation process.

The turbidity removal by the flocculation process can be directly attributed to improved coagulant dosage. The Nigerian Drinking Water Standards (NDWS) recommends a turbidity of an upper limit of 5 NTU. The result of the study also show clearly that the average coagulant dose is effective coagulation of the raw water. Hence there is significant change in levels of raw and treated water turbidity and this is as a result of the coagulation properties of the alum which is able to settle most of the particles in the raw water within a short time.

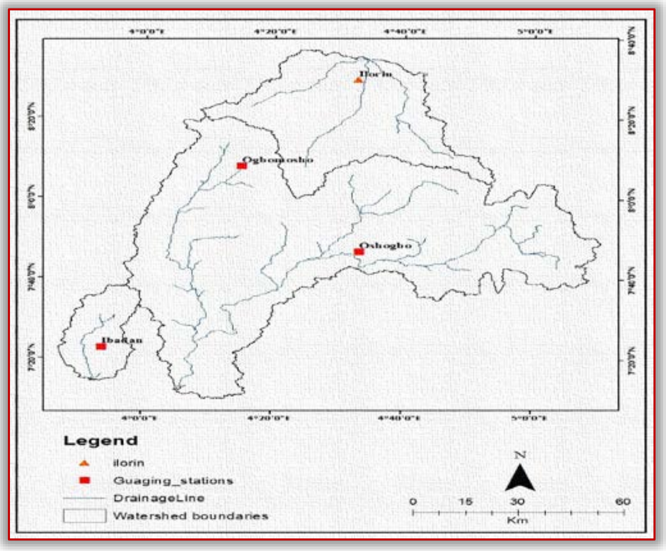

Figure 2. Gauging stations and Asa watershed

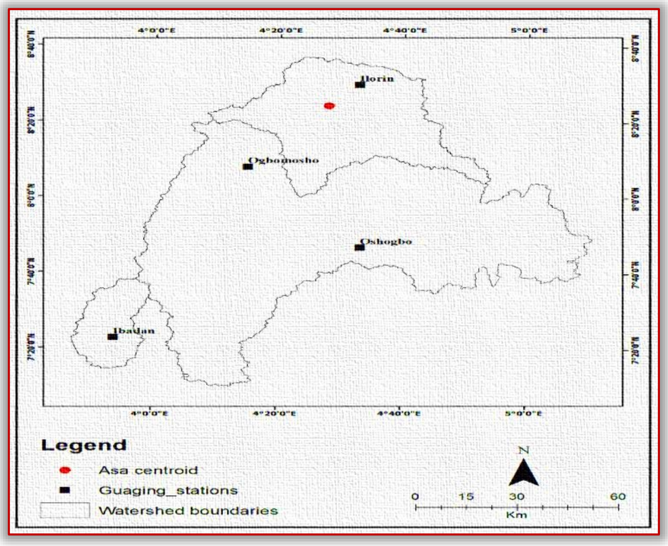

Figure 3. Centriod and the rainfall gauging stations

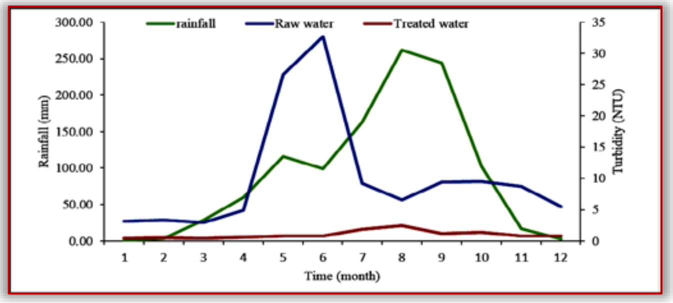

Figure 4: Trends of rainfall, raw and treated water turbidity (NTU)

REGRESSION STATISTICS

Tables 1 and 2 show the Summary of Regression Statistics Model and the Analysis of Variance (ANOVA) respectively. The Multiple regression analysis (MRA) showed a high R^2 value of 73.1% (Table 1). The all-inclusive model generated from the stepwise regression analysis which is a useful approach to understand how the output of water treatment processes are affected by some parameters such as rainfall, raw water turbidity, coagulant dosage and retention time. These three component parameters are strong predictors for determining the treated water turbidity which can be refer to as the plant efficiency. The model derived is valid at 95% level of significance. Coagulant dosage, rainfall and raw water turbidity made significant contribution to the prediction of treated water turbidity. Coagulant dosage is positively related to the treated water turbidity. This could be as a result of effectiveness of Alum. Rainfall is positively related to the treated water turbidity. This could be as a result of climate change that affects the pattern of rainfall. The retention time of water at the sedimentation basin is not significant at 5%. This implies that it did not make much significant contribution to the treated water turbidity.

The multiple correlation coefficient of 0.85 indicates that the correlation among independent and dependent variables is positive. The coefficient of determination, R^2, is 73.1%, which implies that close to 73% of the variation in the dependent variable is explained by the independent variables. The standard error of the regression is 0.40, which is the estimate of the variation of the observed treated water turbidity about the regression. The regression model formulated is presented in Equation 4.

$$Y = -1.5491 + 0.0764X_1 + 0.0047X_2 - 2.2408X_3 - 0.0463X_4 \quad (4)$$

The treated water turbidity was modelled for Asa dam WTP using MLPNN and RBFNN models. The percentage of data used for model training and testing was 83.3% and 16.7%. The correlation coefficients (r) for treated water turbidity using MLPNN is 0.87 while that of RBFNN is 0.97. The plots of the actual and modelled treated water turbidity using MLPNN and RBFNN are presented in Figs. 5 and 6 which indicate strong relationships between the actual and modelled treated water turbidity at the station. RMSE and MRE for training and testing using MLPNN approach are 1.0242, 0.2665 and 0.4827, 1.0208 respectively while that of RBFNN were 0.8735, 0.4669 and 1.6352, 0.6213 respectively. The RMSE for the training and testing using the two NN approaches at the station varied between 0.2665 and 1.0242 while the MRE for training and testing ranged between 0.4827 and 1.6352. The results obtained for RMSE and MRE for treated water turbidity modeling are comparable with what was obtained in similar study as reported by Możejko and Gniot [5].

Table 1: Summary of Regression Statistics Model

Multiple R	R Square	Adjusted R^2	Standard Error	Observation
0.85	0.73	0.58	0.40	12

Table 2: Variance Analysis (ANOVA) treated water turbidity

Sample	DF	SS	MS	F	SF
Regression	4	3.09	0.77	4.75	0.04
Residual	7	1.14	0.16		
Total	11	4.23			

DF=Degree of freedom, SS=Sum of square, MS= Mean of square, F=F-test statistic, F Significance = p-value

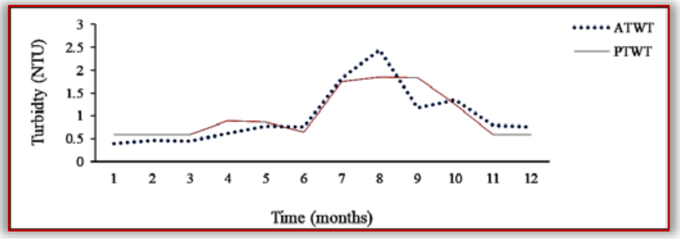

Figure 5: Actual and predicted treated water turbidity using MLPNN

Note: actual treated water (ATWT) and predicted treated water turbidity (PTWT)

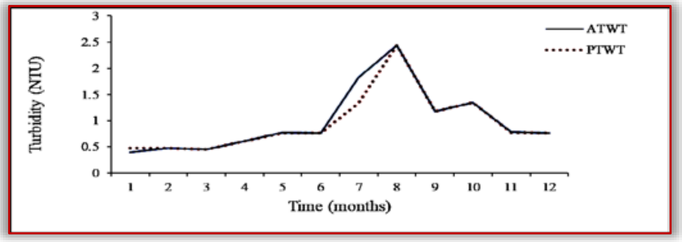

Figure 6: Actual and predicted treated water turbidity RBFNN

Note: actual treated water (ATWT) and predicted treated water turbidity (PTWT)

CONCLUSIONS

The important objective WTP is its effective physical removal of colloidal particles, microorganisms and other particulate materials. Because of low concentration of suspended material in drinking water, turbidity has traditionally been the main water quality parameter for assessing particle removal in water treatment facility. The comparison of the water quality before and after the treatment revealed that Physico-chemical and microbial constituents were below the Nigerian Drinking Water Standards (NDWS). The regression analysis showed that the regression equation for treated water turbidity is good. It was found that coagulant dosage, rainfall and raw water turbidity are significant at 5% level. However, retention time in the sedimentation tanks is not significant at 5% level. Modeling the treated water turbidity using MLPNN and RBFNN approaches revealed that the two modeling methods were able to simulate the parameter adequately with correlation coefficients varying between 0.87 and 0.97. The performance evaluation of the model using correlation coefficients, MRE and RMSE showed that the application of the two NN approaches to simulate treated water turbidity gives satisfactory results for the two NN modeling approaches. Hence the two NN modeling approaches are efficient tools and useful alternatives for simulation of water quality parameters. It is very important to mention that this study can serve as baseline information for further research to help in the monitoring the turbidity removal and other water quality parameters at WTP before supplying potable water for domestic use. The modeling results indicated that reasonable prediction accuracy was achieved for both the regression analysis and ANN models.

The prediction of the aerodynamic coefficients of the investigated projectiles shown in Fig. 1 was carried using the methods and the computer programme described above. The effects of forebody and afterbody shapes on the aerodynamics at supersonic speeds are analysed in this paper.

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