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Performance evaluation of adaptive neuro-fuzzy inference system for modelling dissolved oxygen of Kubanni Reservoir: A case study in Zaria, Nigeria

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Abstract

Background: Water quality evaluation require arduous laboratory and statistical analyses comprising of sample collection and sometimes transportation to laboratories, which may be expensive. In recent years, there has been an emergent need to monitor the dissolved oxygen (DO) concentrations of Kubanni reservoir as a result of anthropogenic and agricultural pollution. Hence, this study was conducted to apply adaptive neuro-fuzzy inference system (ANFIS)-based modelling in the prediction of DO of Kubanni reservoir.

Methods: Water quality data for seven years were used to develop ANFIS models. Six water quality parameters, namely, total dissolved solids, free carbon dioxide, turbidity, temperature, manganese, and electrical conductivity, were selected for analysis based on their sensitivity. Subtractive clustering and grid partitioning techniques were considered when generating the fuzzy inference system (FIS). Three ANFIS models according to different lengths for training data and testing data were selected for modelling.

Results: The results showed that Model-1 gave the best correlation (R-squared and adjusted R-squared of 0.852503 and 0.845000, respectively) for whole data using six input variables. While Model-3 gave the best correlation (R-squared and adjusted R-squared of 0.807791 and 0.799940, respectively) for whole data using three input variables.

Conclusion: The performance efficiency of ANFIS model 1 using 6 inputs shows that the model is reliable for modelling water quality.

Keywords: Dissolved oxygen, Water quality modelling, Manganese, Nigeria

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Introduction

Water quality is simply the chemical and physical properties of water along with the biological properties. These characteristics collectively determine the overall water quality and the fitness of the water for a specific use. These properties are either due to suspended and dissolved substances or inherent in water. Water quality is often defined based on its proposed use (domestic, industrial, or agricultural). The concept that water is always accessible has been discovered to be incomplete. Accessibility of water may not necessarily equate to usability or adequacy.

Safe drinking water is essential for the health development of any region. In some areas, proper management of water resources and good sanitation can boost the economics by reducing diseases and the cost of medical care. This is evident for small and big water infrastructure investments (1). History suggests that intermediations in improving access to potable water are more beneficial to the poor, whether in rural or urban areas. Hence, the availability of safe water is a key to tackling poverty (1). Water quality is necessary to maintain a healthy standard of living for all living organisms, however, this objective is threatened due to urbanization (2).

A mathematical model is a system inter-relating in a given time reference an input, stimulus, information, and output. No general model can be applied to every problem, and in reality, it may be inappropriate to have a general model (3). The model should be built to address a specific problem and this should be reflected in the model characteristics, which include the nature of the data and system familiarity (3). There are various tools used to analyze and develop models. These modelling techniques include correlation data method, regression analysis, principal component analysis, and least squares (4). They can identify concealed and complex interactions between the parameters of the source and drinking water, and hence, predict water quality based on the source parameters (4). Models are used to assess the current state of the water for the presentation of hydrological responses of a catchment, based on previous meteorological and hydrological records. Models are also used to predict future conditions of hydrological responses which may develop due to urbanization, increase in agriculture and land use, climatic change or any physical modification to the land surface, which may be natural or anthropogenic-induced.

Modelling of water quality is the basis for controlling water pollution because it forecasts water quality variation based on the current conditions (5). Understanding the changes in water quality is critical to reduce and regulate water pollution (6). Most countries around the world have started to develop environmental water management schemes to truly understand the quality of the marine ecosystem (6). Hence, routine analysis of the quality of water can ensure that there is a universal guideline in water quality monitoring, thus, conserving the quality of fresh water.

The quality of water may deteriorate when stored in the reservoir. Furthermore, pollution which may be point or non-point may also affect the water quality in the reservoir (7). Artificial intelligence (AI) is an effective tool for monitoring water quality variations and modelling of water quality (6,8). Conventional models hardly cope with the interactions and processes taking place (internal mechanisms), but rather model water quality via inputs and outputs relationships (5,9). AI techniques, however, are more precise in the simulation and forecasting of complex interactions (9). Thus, AI is used extensively in water-related areas for prediction (5,9). Fuzzy logic, artificial neural networks (ANNs), and adaptive neuro-fuzzy inference systems (ANFISs) are examples of AI that have seized the attention of researchers (5,8). However, the technique depends on the nature of the inputs (8).

The fuzzy logic technique uses experimental if-then rules to create quantitative input and output interactions among variables (8). However, the main challenge with fuzzy logic models is that they need expert knowledge to efficiently assign membership function. On the other hand, ANN can learn and adapt to an input and output interaction (8). Although ANN is an outstanding modelling tool, it has some limitations. ANN struggles to analyze inaccurate or ambiguous data (5). Considering these, the ANFIS as a hybrid technique, has captured the attention of researchers in predicting water quality (8). ANFIS combines the ability of the ANN and fuzzy logic in a framework. It, therefore, eliminates the challenge of defining the membership functions and uses the learning ability of ANN for automatic fuzzy if-then rule creation and variable optimization (8). Hence, compared to the ANN, the ANFIS model is more accurate and reliable for prediction (5). Therefore, the ANFIS combines the exceptional learning algorithms of the ANN and excellent prediction functions of fuzzy logic to solve non-linear and complex problems (10).

ANFIS was used to predict the water quality index (WQI) using water quality data collected from rivers and lakes in India between 2005 and 2014. The results suggest that the ANFIS model accurately predicted WQI during the testing phase with a regression coefficient of 96.17% (6).

ANFIS modelling was applied to predict the WQI of River Satluj (Northern India). Water quality data collected from eight different monitoring stations from 1996 to 2012 was used to model (8). Two clustering techniques, fuzzy C-means or FCM-ANFIS and subtractive clustering or SC-ANFIS, were used to estimate and predict the WQI using seven water quality parameters. The parameters include pH, conductivity, Chlorides, Nitrates, Ammonia, and fecal coliforms. Based on the statistical performance, the subtractive clustering technique showed higher accuracy compared to fuzzy C-means. The subtractive clustering model was then used to identify sensitive parameters that could significantly change the WQI (8).

The concentrations of cadmium (Cd) in the Filyos River, Turkey, were predicted using ANFIS. The obtained data set comprises of water samples collected from seven sampling locations from 2014 to 2015. The results showed a high degree of accuracy and robustness with correlation (R^2=0.91) between observed and predicted concentrations (10).

Furthermore, monthly input data for dissolved oxygen (DO), pH, biochemical oxygen demand, and water temperature was used to model the DO concentration (downstream of Agra city) at three different places along the Agra upstream, middle stream, and downstream. The efficiency of the models showed that ANFIS effectively modelled the DO concentration (9).

The ANFIS approach was used to detect the best ANFIS model out of three, which satisfied Root-Mean-Square Error and R^2 during training and testing using groundwater quality index data (1997-2006) of Matar Taluka and Nadiad Taluka. ANFIS model-2 and ANFIS model-3 effectively modelled Matar Taluka and Nadiad Taluka groundwater quality index respectively with the highest efficiencies (11).

The aim of this study was to examine the performance of ANFIS in the prediction of DO of Kubanni Reservoir, Zaria, Nigeria.

Materials and Methods

Study area

The Kubanni drainage basin flows from the environs of Ahmadu Bello University Main Campus. The river flows southeast through Ahmadu Bello University from the Kampagi Hills (Shika) into River Galma in the southwest direction. It passes several research institutions, and rural and urban settlements before draining into the Kubanni Reservoir. In 1973, to provide water for the growing population, the university authorities dammed the river at about 7.25 km from the source (12). The stretch of the reservoir falls between Latitude 11°08'21.57" N to 11°07'54.86" N and Longitude 7°38'57.44" E to 7°39'28.67" E (Google Earth, 2021). Figure 1 shows the satellite image of the study area.

Data collection

Six water quality parameters were selected for analysis based on their sensitivity. The data were collected from January 2014 to December 2020 from Ahmadu Bello University Water Works. The parameters include total dissolved solids, free Carbon dioxide, turbidity, temperature, Manganese, and electrical conductivity. The latitude and longitude of the sampling location are at 11° 8'26.55"N and 7°39'20.91"E, respectively. The mean data of three-year data of the same month were used to correct the missing values (13). The water quality parameters were tested in triplicate according to the Nigerian standard for drinking water quality (NSDWQ) recommended centralized scheme.

ANFIS mechanism

The ANFIS is a multilayer feed-forward network, which was first proposed by Jang (14) to create an input-output mapping using ANN learning algorithms and fuzzy logic. Therefore, making it more efficient for common methods in generating complex time series (5,8).

There are two fuzzy inference systems (FIS) commonly used for mapping input to an output. These systems include Mandani Inference System and Sugeno Inference System (8,9). Based on the various fuzzy rules, aggregation and defuzzification procedures differ (8). Mandani rule requires de-fuzzification while the Sugeno process does not (9). However, studies have shown that compared to the Mandani's system, the Sugeno structure is more compact and computationally efficient, with either first-order or zero-order Sugeno FIS (8).

According to (6), the ANFIS model is used to explain non-linear and complex problems because it syndicates the gains of fuzzy logic and ANN to automate fuzzy if-then rule generation and parameter optimization (11). Fuzzy logic and fuzzy rule are mathematical expressions that handle uncertainty, imprecision, and vagueness between the input and the output as a result of an if-then statement and language variable (15,16).

The ANFIS like other soft computing tools has its limitations (17). The dataset for ANFIS modelling first undergo normalization. Normalization of water quality parameters is necessary to reduce noise due to significantly larger numbers by scaling the data in the same array, and therefore, hastens the training process (9).

The ANFIS algorithm is used to predict data and obtain the optimal membership function through the input layer adaptive system (6). The key components of ANFIS are fuzzy database, defuzzifier, and fuzzifier while the

Figure 1. Satellite image of the Kubanni Reservoir, Zaria, Nigeria (Source: Google Earth Map, 2021)

conceptual components of the ANFIS are inputs and output database, fuzzy system generator, FIS, and adaptive neural network (7). The ANFIS model comprises of five layers, namely, fuzzification, antecedent, strength normalization, consequent, and inference, containing many nodes (6,18).

The ANFIS model is represented by two input parameters and one output parameter (6,8), as shown in Figure 1. The if-then rules are applied in equations 1 and 2:

$$Rule1: if\ x \text{ is } A_1 \text{ and } y \text{ is } B_1,\ then \quad (1)$$
$$Rule1: if\ x \text{ is } A_2 \text{ and } y \text{ is } B_2,\ then\ f_1 = p_2 x + q_2 x + r_2 \quad (2)$$

Where x and y are the node i input parameters, A_1, A_2, B_1, and B_2 are the fuzzy set, p_1, p_2, q_1, q_2, r_1, and r_2 are the consequent parameters, and f is the output.

Layer 1 - Fuzzification Layer: This layer implements a membership function to change the input data into a fuzzy set.

$$O_{1,i} = \mu A_i(x) \text{ for } i = 1,2 \quad (3)$$

$$O_{1,i} = \mu B_i(y) \text{ for } i = 1,2 \quad (4)$$

$$\mu A_i(x_1) = \frac{1}{1 + \left(\frac{x - c_i}{\sigma_i}\right)^{2b_i}} \quad (5)$$

Where $\mu(x)$ and $\mu(y)$ are membership functions, A_i is the linguistic variable, while σ_i, b_i, and c_i are the parameters of the Bell function.

Layer 2 - Antecedent layer: Nodes in the second layer are fixed nodes where inputs from the previous layer are multiplied with the node value to form an output signal for the second layer.

$$O_{2,i} = w_i = \mu A_i(x) * \mu B_i(y), \text{ for } i = 1,2 \quad (6)$$

Where w_i signal refers to the firing strength of the rule.

Layer 3 - Strength normalization layer:

The ratio of i_{th} is calculated to normalize firing strength.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \text{ for } i = 1,2 \quad (7)$$

Where $O_{3,i}$ is the output of layer 3 and $\overline{w}$ is the normalized firing strength.

Layer 4 - Consequent layer: The nodes of the fourth layer are adaptable, and the output of this layer is $O_{4,i}$. The node function of the fourth layer is defined in Eq. (8):

$$O_{4,i} = \overline{w}_i . f_i = \overline{w}_i . (p_i x + q_i x + r_i) \quad (8)$$

Where p_i, q_i, and r_i are consequent parameters used for the FIS function (f_i).

Layer 5 - Inference layer: This layer is applied to obtain the model output. The final output of a network is described in Eq. (9):

$$O_{5,i} overall\ output = \sum \overline{w}_i f_i = \frac{\sum_i \overline{w_i f_i}}{\sum_i w_i} \quad (9)$$

ANFIS modelling

It is necessary to select a suitable combination of input variables for modelling (8). As a result, the sensitive parameters were used to model the water quality parameter (5,8,12).

Data preprocessing was done using the linear normalization technique to make the array between 0 and 1. Linear normalization is mathematically expressed in Eq. (10).

$$x_i^*(k) = \frac{\max x_i(k) - x_i}{\max x_i(k) - \min x_i(k)} \quad (10)$$

Where $i = 1,2,3,\ldots, m$ and $k = 1,2,3,\ldots, n$. Values m and n are the number of experimental data and responses, respectively. $x_i(k)$ and $x_i^*(k)$ represent the original sequence and the sequence after the data preprocessing, respectively. max $x_i(k)$ is the largest value of $x_i(k)$, and min $x_i(k)$ is the smallest value of $x_i(k)$, while x is the desired value (19).

MATLAB Neuro-Fuzzy Designer was used to model the water quality. The water quality data were grouped into two sets, training (to train ANFIS) and testing (to assess the model performance). The main computation in the ANFIS consists of four processes. The first phase was to load the data. Then, FIS was generated. Subtractive clustering and grid partitioning techniques with Gaussian membership functions were used to generate FIS. Thirdly, the training function was used to learn the input data, and errors were gathered. The ANFIS training is iterative to compute the best values by diminishing the sum of squared differences between training data values and predicted values. The hybrid learning algorithm was used to train the FIS for 100 Epochs. The training process continued until errors maintained stability. The final stage was to predict the output.

Results

Basic statistics

Table 1 shows the summary of the basic statistics of the variables (parameters).

Dissolved oxygen ANFIS model

The parameters used to model the DO were selected based on their sensitivity (5,7,11). These parameters significantly influence the water quality variation of Kubanni Reservoir (11). First, the entire 6 sensitive parameters (total dissolved solids, free carbon dioxide, turbidity, temperature, Manganese, and electrical conductivity) were used as input variables (12). Then, three sensitive parameters (manganese, temperature, and turbidity), which have higher absolute loading factors, were used as input variables (12). Three ANFIS models were selected by varying the training and testing data to model the DO as follows:

- ANFIS: 50%-50% (Model-1)
- ANFIS: 70%-30% (Model-2)

Table 1. Basic statistics of water quality data

Parameter	Mean	Max.	Min.	Range	Var.	±SD	Drinking water guidelines NSDWQ
TDS (mg/L)	53.90	93.70	13.20	80.50	439.50	±20.90	<500
FC (mg/L)	21.80	114.00	10.00	104.00	284.90	±16.90	-
Turbidity (NTU)	1439.90	17372.00	15.10	17357.00	1.30E+7	±3572.10	5
Temp. (°C)	25.90	39.50	17.70	21.80	12.80	±3.60	<40
Mn (mg/L)	0.10	0.30	0.01	0.29	0.01	±0.05	<0.2
EC (µS/cm)	90.40	156.40	21.50	134.90	1237.20	±35.10	<1000

FC = Free carbon dioxide; Temp. = Temperature; Max = Maximum; Min = Minimum; Var = Variance; SD = Standard deviation; NSDWQ: Nigerian standard for drinking water quality (NIS 554:2007). TDS = Total Dissolved Solids; FC = Free carbon dioxide

Table 2. Performance characteristics of the ANFIS model for testing, training, and whole phase

No. of inputs parameters	Phase	Correlation coefficient	Model-1	Model-2	Model-3
Six	Training	R^2	1.000000	0.999862	0.952900
		Adjusted R^2	1.000000	0.999860	0.952227
	Testing	R^2	0.568100	0.483600	0.612490
		Adjusted R^2	0.567910	0.483581	0.612000
	Whole	R^2	0.852503	0.726430	0.626910
		Adjusted R^2	0.845000	0.713400	0.626700
Three	Training	R^2	0.803087	0.919964	0.839604
		Adjusted R^2	0.790664	0.913411	0.833027
	Testing	R^2	0.378000	0.625400	0.766000
		Adjusted R^2	0.361989	0.624400	0.762190
	Whole	R^2	0.487400	0.737220	0.807791
		Adjusted R^2	0.462600	0.736610	0.799940

- ANFIS: 80%-20% (Model-3)

Table 2 summarizes the prediction results of DO obtained by the ANFIS models during the training, testing, and whole stage. The higher R^2 and adjusted R^2 for different membership functions and varying combinations of the variables were estimated. The subtractive clustering partitioning technique produced better outputs with 6 input parameters while the grid partitioning technique produced better outputs with 3 input parameters.

Considering the whole data, Table 2 shows that Model-1 with R^2 and adjusted R^2 of 0.852503 and 0.845000, respectively, provides the best output for the prediction of DO. When considering 6 inputs, Model-3 provides the best output for 3 inputs with R^2 and Adjusted R^2 of 0.807791 and 0.799940, respectively. The relationship between observed and predicted values is illustrated in Figures 2 and 3.

Discussion

Figure 3 suggests that observed and predicted values from the Model-1 using 6 input variables are in close agreement compared to the Model-3 using 3 input variables in Figure 3. Furthermore, the R^2 and Adjusted R^2 indicates that Model-1 using 6 input variables predictions are closer to the observed values compared to the Model-3 using

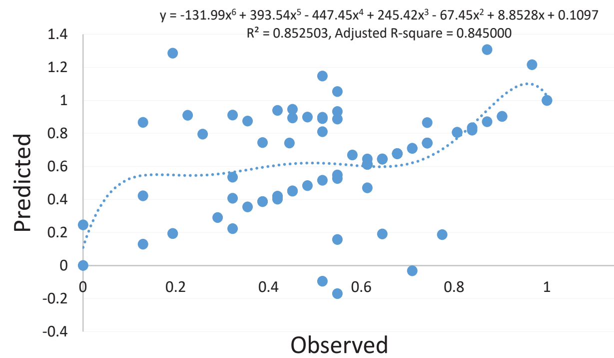

Figure 2. Observed vs. predicted Model-1 using 6 input variables for the whole data

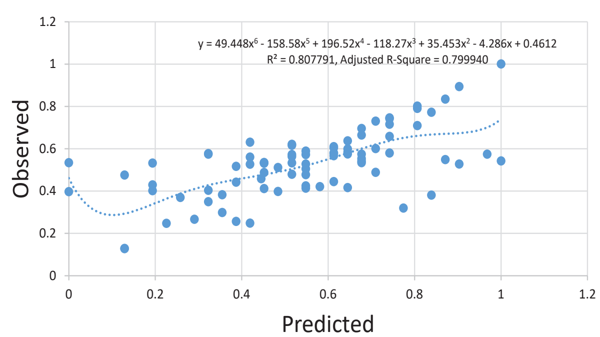

Figure 3. Observed vs. predicted Model-3 using 3 input variables for the whole data

3 input variables. Hence, sensitive parameters are the indication of variation in water quality.

The comparatively high correlation between observed and predicted values was detected for training data, which is similar to that reported by other studies (5,6,8-10). However, a significantly lower correlation was established between the observed and predicted testing values. Singh (20) and Nemati et al (21) also found a relatively lower correlation from the ANFIS model between the observed and predicted values of DO. This might be due to the extended sampling period, the nature of sampling locations, and the heterogeneous nature of the water quality (20).

Conclusion

The performance efficiency of ANFIS model 1 using 6 inputs (R^2 and Adjusted R^2 of 0.852503 and 0.845000, respectively) shows that the technique is reliable for modelling water quality. However, other AIs are recommended for further studies in the modelling of water quality. Therefore, this study can constitute a basis for monitoring the DO concentration in the Kubanni reservoir.

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Ethical issues

The study was approved by the Department of Water Resources and Environmental Engineering, Ahmadu Bello University, Zaria-Nigeria, on September 2, 2021.
The authors declare that they have no conflict of interests.

Competing interest

The authors declare that they have no conflict of interest.

Authors' contributions

Conceptualization: Eneogwe Chukwuemeka, Abubakar Alfa Umar.
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Methodology: Eneogwe Chukwuemeka, Abubakar Alfa Umar.
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Writing – original draft: Eneogwe Chukwuemeka.
Writing – review & editing: Eneogwe Chukwuemeka.

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