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River Water Quality Prediction Using Adaptive Neuro-fuzzy Inference System and Artificial Neural Network Modeling: A Review

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Abstract

Water is the source of life and rivers, the main source of water are vital for all aspects of ecosystems and also, for human health. In order to control the water quality environment more accurately, artificial intelligence (AI) is applied to increase the preciseness of the water quality prediction. The implementation of AI viz. adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) in predicting river water quality parameters is quite new in the whole wide world but it is slowly replacing the traditional techniques in forecasting the major parameters of surface waters. Although the classical methods still can be used but it may not give outputs and results that are more accurate than the ANN and ANFIS. Therefore, this paper is a review aimed at how ANN and ANFIS can improve in evaluate the river water quality than the traditional techniques used before.

1. INTRODUCTION

Water as the source of life for humanity [1] and rivers, the supreme source of water [2] are important matter for all aspects of ecosystem and human health [3]. Rivers are free from any impurities or contaminants at the initial stage and are considered the most clean water resources in all over the world. Since there are rapid increased in human, urban and industrialization development, it have caused the rivers to loss their sustainability [4]. Furthermore, the possibility of a contaminant and pollutant being dumped to the rivers as industrial and municipal waste is always concern to those using and diverting water from rivers [5].

Water quality prediction or forecasting is important in aquaculture, sustainability, ecosystem and environmental monitoring [6]. The description of the biological, chemical and physical characteristics of water and its ability to be sustained for a specific use is how water quality be defined [7]. Determining the surface water quality and analysing water quality elements are vital aspects in the analysis of any aquatic system for a sound management of the river basin. Therefore, predetermined measures can be taken to mitigate pollution or containment within the acceptable tolerance level [8]. Moreover, river water quality usually changes due to drastically increased nutrient materials and chemicals which will threaten the aquatic ecosystem and the river downstream environmental conditions [9].

In the evaluation of water quality, multivariate statistical techniques have been utilized to identify the prime factors that affecting water quality and to understand water quality of various field of study. Factor analysis (FA), cluster analysis (CA), discrimination analysis (DA) and principal component analysis (PCA) are the examples of multivariate statistical techniques which were considered as the traditional approaches [10]. Therefore, the application of AI models have lately been used in various hydrological related studies in order to overcome the disadvantages of these traditional approaches [11]. The application of the new method, AI which is an adaptable mathematical framework has the ability to identify the complex non-linear relationship between an input and output variables as compared to the traditional methods previously being used [12]. The forecasting and prediction of the major parameters of surface waters is usually performed using different types of AI based methods relying on machine learning where it requires training, validating and test sets [13].

Nowadays AI, namely ANFIS and ANN have become gradually famous for forecasting and predicting in various areas such as environmental science and water resources

[14]. Countless researchers have used ANN method to forecast water quality parameters in the river systems [15]. Shortages of reliable water quality data and high cost incurred in water monitoring process are among the major obstacles in process-based modeling techniques. ANN on the other hand gives a particularly good option [16]. It have also been successful used in several studies focusing on water quality forecasting in waste water treatment plants, lakes, reservoir and in rivers too [17]. Furthermore, ANN has the ability to map non-linear relationships of the aquatic ecosystem's characteristics compared to the assumption made by the classical water quality techniques that give a linear relationship between predicted and response parameters together with their normal distribution [18]. On the other hand, ANFIS is defined as the combination of fuzzy inference technique whereby the parameters are determined by the neural network learning algorithms and adaptive neural network. It recognizes a set of variables via hybrid learning rule which combines least squared error method and back propagation gradient descent error digestion. It also has the ability to estimate some real continuous function on a compact set to some degree of accuracy [19].

The remaining part of this paper contains following 5 sections: An overview of ANN modeling of river water quality parameters is described in Section 2, Section 3 provides an overview of ANFIS modeling of the river water quality parameters. A review about the previous studies of river water quality parameters modeling using ANN and ANFIS are discussed in Section 4 and Section 5 provides the conclusion of this study.

2. MODELING OF RIVER WATER QUALITY PARAMETERS USING ARTIFICIAL NEURAL NETWORK (ANN) - AN OVERVIEW

Usually, Feed-forward Neural Network (FFNN), Back-propagation Neural Network (BPNN), General Regression Neural Network (GRNN), Support Vector Machine (SVM) and Multilayer Perceptron (MLP) are ANN architectures that have been applied by various researchers to predict river water quality.

Eventhough the conception of artificial neurons was initially introduced in 1943, further research into the application of backpropagation training algorithm for the feed-forward artificial neural network was only increased sustaintially in 1986. Comparatively, ANN can be considered as a quite new instrument in the study of forecasting and prediction [20]. Artificial Neural Network or ANN modeling for short can be applied to overcome problems that are not amenable to mathematical and traditional statistical methods since it is a nonlinear statistical methods [21]. The model also able to understand the difference in information and able to offer a pleasing solution and can be carried out as a software in computers or as hardware in an electronic circuitry. Artificial neural cells are connected to each other with different connecting geometries which defined ANN as a complex systems since it was inspired by a human brain structure. Even though the neural networks does not have certain input value and the fact that it never have seen the input before, it still be able to detect similarities in inputs. Therefore, this features gives an excellent interpolation capabilities especially when several inputs data is not exact or incorrect [22].

Normally, the basic architecture of ANN comprise of three distinctive layers, namely input layer, hidden layer and the output layer. The initial layer is where the data is introduce to the model, then the data are processed in the middle layer and the outcome produced by the model is located in the last layer. Trial and error method usually used to decide the number of input layers and one hidden layered network is the most frequent [23]. The one that gives the model with its stability to generalize is also the hidden layers [24]. Output layer is where the outcome is produced by ANN [25] and each layer is connected to the next layer by nodes or also known as neurons [26]. Furthermore, all neurons in hidden and output layers except for input layer are made up of various components, namely weights, an activation function and also the offset or mainly known as bias [27]. A specific mathematical function in each neuron/node called activation function will accept inputs from previous layers and then generate output for the next layer [28]. Transfer functions that normally used by many researchers are the linear, hyperbolic tangent or the sigmoid function [29] but sigmoid transfer functions usually used in hidden layers of the multilayer networks [30].

3. MODELING OF WATER QUALITY PARAMETER USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) - AN OVERVIEW

ANFIS, well known machine learning model is a multi-layer feed-forwardneural network [31] composed of two different models, namely the fuzzy logic (FL) and ANN. Nonlinear and linear are the two types of parameters which are adjusted during the training process that ANFIS model possesses. FIS is an ensemble of logical rule-based and it transforms the input parameters using membership functions. Thus, it shows that the rule bases are composed from the membership functions' (MFS) results [32]. It uses a learning algorithm of fuzzy logic systems and neural network to give a nonlinear depiction of the input-output relationship [33]. Mamdani's, Sugeno's and Tsukamoto's systems are where most FIS been catagorized into. This depends on the classification of inference operations upon if-then rule [34] Although Mamdani's sytem is the most commonly applied but Sugeno's system is the most well-known candidate regarding sample data that based on fuzzy modeling since it gives crisp output, more compact and computionally structured [35].

Moreover, ANFIS has showed to be powerful in modeling various processes such as real-time reservoir operation and power systems dynamic load [36] since it has the ability to combine the verbal power of fuzzy system with the numeric power of neural system adaptive network [37]. There are five layers in the architecture of ANFIS. In every layer holds various nodes that is described by the node fuction [38]. There are several types of membership functions that have been used in ANFIS from previous studies, namely bell-shaped (MFgbell), triangular (MFtri), spline-based (MFpi) or piduetoits and also Gaussian (MFgauss) [39].

4. RIVER WATER QUALITY MODELING USING ANN AND ANFIS - A REVIEW

FFNN with or without back-propagation (BP), GRNN, SVM, BPNN, radial basis function neural network (RBFNN) and multilayer perceptron (MLP) are methods in the ANN modeling that usually chosen by researchers to predict water quality parameters viz. dissolved oxygen (DO), temperature, biochemical oxygen demand (BOD), chemical oxygen demand (COD), total dissolved solid (TDS), pH value, turbidity, electrical charge (EC) or water quality status according to the authors specific research. Different statistical measurements such as determination of coefficient (R^2), mean square error (MSE), average absolute relative error (AARE), mean absolute error (MAE), root mean square error (RMSE), correlation coefficient (*R*), Nash-sutcliffe coefficient of efficientcy (NSCE), mean absolute percent error (MAPE) and coeffiecy of efficientcy (*E*) are normally used by the authors to evaluate their models refer to the objectives that they have set to achieve.

With input data namely, temperature, DO, water flow, Chlorophyll-a, COD and nutrients (ammonia, nitrite and nitrate) that measured from 2001-2002, Dogan et al., 2009 [21] applied FFNN to compute BOD model at Melen River, Turkey. To evaluate the performance and robustness of the model, R^2, MSE and AARE were chosen. The outcomes from this research stated that COD was more influenced on the BOD prediction since both (COD and BOD) are indicators of oxygen consumption from degradation of organic materials. The authors also stated that having 8 data inputs together with 1 hidden layer that has three nodes gives the best choice for the ANN model. Singh et al., 2009 [18] also used FFNN but with BP in their research. It was conducted in Gomti River, India to compute BOD and DO levels. The authors used monthly data for a period of ten years of 13 water quality parameters viz. total alkalinity (T-Alk), total hardness (T-hard), total solid (TS), chloride (Cl), phosphate (PO_4), potassium (K), sodium (Na), ammoniacal nitrogen (NH_4-N), nitrate nitrogen (NO_3-N), COD , 5-day BOD , DO and pH for the ANN modeling. The model's performance was evaluated using R^2, RMSE and bias and Lavenberg-Marquardt algorithm was applied to train both constructed models. The outcomes showed both models gave a best fit model for training, validating and test data sets. For instance, R^2, RMSE and bias values obtained for testing was 0.76, 1.23 and -0.43 while 0.77, 1.38 and -0.22 for DO and BOD models, respectively. Ahmed, 2017 [17] choose RBFNN and FFNN models to forecast DO in Surma River, Bangladesh using COD and BOD as the input data that have been collected during 3 years study. MSE, *R* and *E* were applid to determine the performance of both models. The authors has stated RBFNN has higher accuracy than FFNN in forecasting the DO concentrations in the river and RBFNN that contains all input data was the most suitable model in DO concentration prediction since the MSE, *R* and *E* values were 0.654, 0.944 and 0.936, respectively for the whole array data set.

Commonly, MLP model were applied by most researchers to predict whether COD, DO, TDS, pH value, turbidity or EC in their studies. Kanda, et al., 2016 [23] used data input consist of four input variables, namely turbidity, pH, EC and temperature with 113 of monthly value from 2009-2013. The authors used the MLP model to predict DO in River Nzoia, in Lake Victoria Basin, Kenya and applied R^2 and RMSE to assess the performance of the model. The authors concluded that ANN model can be used to predict DO at the river since values obtained ranging from 0.34 to 0.64 mg/l and 0.79 to 0.94 for RMSE and R^2, respectively. Nemati and Naghipour, 2014 [40] also used this model to predict TDS in Sinineh River, Iran using water discharge (Q), sulphate (SO_4), bicarbonate (HCO_3), sodium (Na), magnesium (Mg), chloride (Cl) and calcium (Ca) as input parameters. The input data was from 1993 until 2011. The performance of the model was evaluated using R^2, MSE and RMSE and results have shown that ANN model with 14 hidden neurons was chosen as the best in performance where the value of R^2, MAE and RMSE obtained were 0.841, 16.986 mg/L and 30.119 mg/L, respectively. Almost the same research as conducted by the previous mentioned authors, Niroobakhsh et al., 2012 [41] conducted a research using MLP and RBFNN models to study the capability of it to predict TDS using measured input parameters (for 40 years) such as upstream stations' Q, EC, TDS and downstream stations' EC. The research was done in Jajrood River, Iran and the model was assessed using R^2 and RMSE. Moreover, RBFNN outperformed MLP in prediction with more than 90% accuracy since RBFNN can work well with large number of input data and obtained R^2 values of 0.9362 (validation) compared to R^2 values of 0.8968 (validation) for MLP.

The estimation of daily pH value in Middle Loire River, France was made using MLP by Moatar et al., 1999 [42]. Input data such as solar radiation and river discharge variables were used. In order to verify stationarity and homogeneity, comparison values between the estimated and measured pH values were conducted using statistical test. The outcome achieved by the authors was high in *R* with values of R^2 are 0.88 and 0.86 for calibration and verification sets, respectively. Thus, it can proved satisfactory on the pH simulations when it achieved accuracies of 86%. Furthermore, Najah et al., 2013 [8] have used MLP, RBFNN and linear regression model (LRM) to predict water quality, namely turbidity, TDS and EC in Johor River Basin in Malaysia using five years of observed data from 1998 until 2002. Performance of the models were evaluated based on MAPE, *E* and *R*. The results that they have obtained was that MLP based model outperformed LRM where MAPE of MLP was 19% while MAPE for LRM exceeded 90% in the prediction accuracy of turbidity. Another researched using MLP was done by Ay and Kisi, 2014 [43]. The authors also used k-means clustering method in the COD concentration modeling. Both methods were tested using water quality (daily measured water suspended solid, discharge, pH value, temperature and COD) data of upstream of the municipal wastewater treatment plant system in Adapazari province in Turkey. R^2, MAE, RMSE and mean absolute relative error were the statistical parameters used to assessed the performance of the models. The results achieved showed k-means-MLP (3,1,1) model outperformed the other methods such as MLP, multi-linear regression (MLR), radial-based neural network and generalized regression neural network as comparisons used in the study in estimating COD. The values obtained for k-means-MLP were 59.45, 43.17 and 0.88 for RMSE, MAE and R^2, respectively.

Furthermore, Abba et al., 2017 [4] have used ANN, MLR and ANFIS methods to predict DO concentration in Yamuna River of Agra downstream by using monthly input data which consist of BOD, water temperatures, DO and pH at three different places. The places were Agra downstream, middle stream and upstream. Based on their research, the performance was evaluated using RMSE and R^2. The result showed that both ANFIS and ANN can be applied in modelling DO concentration and results of ANN from middle and downstream was almost better than ANFIS model and MLR model. This is because, the value of DC and RMSE in calibration phase was 0.94 and 0.7, respectively and in the validation phase, the DC and RMSE value was 0.81 and 1.38 respectively. Another researched paper from Arslan et al., 2017 [44] have applied ANN and ANFIS to stimulate TDS at Tigris River at El-Wihda station, Iraq using monthly data obtained from 2009-2013. Water quality parameters, namely hardness, temperature, turbidity, pH, SO_4, EC, Cl and TDS at 8 stations (El-Karkh, El-Wethba, El-Dora, El-Kerame, El-Qadisiye, El-Wihda and El-Rasheed) were used in simulation operation. For the implementation of the models, MATLAB neural network toolbox was used. The authors have chosen Lavenberg-Marquardt Neural Network (LMNN) and Scaled Conjugate Gradient (SCGNN) method as the ANN. Nash-Sutcliffe efficiency (E_{Nash}), percent bias (R_{Bias}), MAPE and R^2 were the statistical performance parameters in this research. The results showed that LMNN has the best result compared to SCGNN with 7 input nodes viz. hardness, temperature, pH, electrical conductivity, SO_4, Cl and turbidity and 10 neurons at the hidden layer. The R^2 and MAPE values for LMNN for test period were 0.999 and 22.67, respectively while for ANFIS, the R^2 and MAPE values were 0.968 and 26.00, respectively.

Kisi et al., 2013 [19] modelled DO using gene expression programming (GEP), ANFIS and three-layer FFNN that were employed with a sigmoid transfer function in the hidden layer and a liner transfer function in the output layer in their research. 14 years (1996-2012) of daily DO concentrations, water mean temperature (Tmean), pH, specific conductance (SC) and Q data were used and obtained from South Platte River at Englewood, Colorado. The statistical assessment parameters to evaluate the model's performance viz. RMSE, MARE, MAE and also *R*. Furthermore, various input combinations of SC, pH, Tmean and Q parameters were tried as inputs to both ANFIS and ANN models to evaluate the degree of effect of each variables on the DO concentration. The results shown that the models with Q, pH, T mean and SC parameters were the best. Next, the optimal GEP model was obtained for the forth input combinations and after being compared with the ANN and ANFIS, it showed that GEP performed much better than the other models in DO concentration modeling. Correlation coefficient of the GEP were 0.850, 0.889 and 0.930 for training, testing and validation, respectively. Yan et al., 2010 [38] also used ANFIS in their research to classify the status of the water quality of all major river basins in China, including Minjiang River, Dianchi Lake, Qiantang River, Taihu Lake, Pearl River, Yellow River, Yangtze River, Haihe River, Huaihe River, Songhua River and Liohe River. Three water quality parameters namely, ammonia-nitrogen (NH_3-N), COD and DO that have been observed weekly from 40th to 48th week in the year 2019 (over nine weeks) were used in this research. Performance of the developed model were assessed using RMSE, E_{Nash} and *R*. The results showed that performance of model 2 (Gaussian) outperformed the other models with value of RMSE, E_{Nash} and *R* testing phase was 0.3704, 0.9316 and 0.9689, respectively. Membership functions viz. Pi, sigmoidal, triangular, generalized bell and trapezoidal were also tested by the authors in their research.

Prediction of another water quality parameters that used ANFIS, MLP/BP and RBFNN was done by Emamgholizadeh, et al., 2014 [34] to predict three water quality parameters such as COD, BOD and DO in Karoon River in Iran with historical data period of 17 years (1995 until 2011). Turbidity, sodium, magnesium, phosphate, nitrate nitrogen, nitrite, pH and EC that have been measured in Karoon River were also used in this model. Performance of these models were evaluated by MAE, RMSE and RZ^2. A sensitive analysis to determine the relative contribution and importance of the input variables was done in this research. Phosphate was known as the most effective variables for the thress water quality parameters based on the outcome achieved by the authors. Lastly, the achievement obtained for MLP/BP model outperformed the other two models since it gave values 0.93, 0.86, 0.95 in training stage and 0.96, 0.85 and 0.94 in testing stage for BOD, DO and COD, respectively.

This clearly shows that any methods used in ANN modeling do achieved results with high accuracy for the previous studies conducted but it depends on the input parameters,

Table 1. Summary of the artificial intelligence approaches for river water quality prediction.

Type of Approach	Methods	Output Parameters	Statistical Evaluation Parameters	Authors
ANN	Three-layer FFNN with BP	BOD and DO	R^2, RMSE and Bias	Singh et al., 2009 [18]
ANN	MLP and k-means clustering	COD	R^2, RMSE, MARE and MAE	Ay and Kisi, 2014 [43]
ANN	RBFNN and FFNN	DO	MSE, E and R.	Ahmed, 2017 [17]
ANN	MLP	DO	R^2 and RMSE	Kanda, et al., 2016 [23]
ANN	MLP and RBF	TDS	RMSE and R^2	Niroobakhsh et al., 2012 [41]
ANN	MLP	TDS	RMSE, MSE and R^2	Nemati and Naghipour, 2014 [40]
ANN	MLP	pH value	R^2 and R	Moatar et al., 1999 [42]
ANN and ANFIS	MLR and ANFIS	DO	RMSE and DC	Abba et al., 2017 [4]
ANN	MLP-NN, RBF-NN and LRM	Turbidity, TDS and EC	MAPE, E and R	Najah et al., 2013 [8]
ANN	FFNN	BOD	AARE, MSE and R^2	Dogan et al., 2009 [21]
ANN and ANFIS	ANFIS, MLP/BP and RBF	BOD, COD and DO	R^2, RMSE and MAE	Emamgholizadeh, et al., 2014 [34]
ANFIS	ANFIS	Classification of water quality status	RMSE E_{Nash} and R	Yan et al., 2010 [38]
ANN and ANFIS	ANFIS and ANN	TDS	E_{Nash}, R_{BIAS}, MAPE and R^2	Arslan et al., 2017 [44]
GEP, ANFIS and ANN	GEP, ANFIS and Three-layer FFNN	DO	RMSE, MARE, MAE and R	Kisi et al., 2013 [19]

number of nodes and hidden layers and statistical parameters chosen to evaluate the models constructed. Since ANFIS is more advanced compared to ANN, it does outperformed ANN and it sometimes depends on the membership functions and the type of statistical measurements used to assessed the accuracy of the model. However, both ANN and ANFIS are way more efficient and high in accuracy than the traditional approaches to measured the river water quality. Table 1 below shows the summary of artificial intelligence approaches such as ANN and ANFIS that have been used by the previous researchers.

5. CONCLUSION

Recently artificial intelligence, namely ANFIS and ANN have become gradually famous for forecasting and predicting in various areas such as environmental science and water resources. Many research investigations and studies on the prediction and forecasting of the river water quality parameters have been reported by researchers from all over the globe. The previous studies discussed in Section 4 confirmed that ANN and ANFIS can be applied and used for modelling and forecasting river water quality parameters.

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