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A Review on Water Pollution Detection Techniques using Artificial Neural Network Methods

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ABSTRACT

Water quality is defined by its physical, chemical and biological parameters which are interrelated. In recent years, Artificial Neural Networks (ANN) have found some applications in the area of water quality modeling. Among the various familiar methods of water pollution detection, ANN based methods are one of the most effective methods which provides satisfactory outcome to the users than other methods. This paper elucidates several techniques for detecting water pollution, as applied in diverse regional water sources, and delineates their respective findings using appropriate formats such as tables and figures. These methods for water pollution detection, along with their corresponding data, figures, tables, and results, are comprehensively presented herein alongside the relevant citations and references. This study will help to understand diverse effective techniques for evaluating water quality and detecting water pollution level. Furthermore, this study will guide for refining and developing improved methodologies within this domain.

General Terms

Water pollution, ANN (Artificial Neural Network).

Keywords

Water quality, prediction, BP (Back Propagation), Feed Forward, contamination, detection.

1. INTRODUCTION

Pure water is one of the most important needs of all lives and the environment. 70% of the earth is covered by the water and also human bodies' main component is water. Sufficient water quality and quantity is one of the key challenges. But resources of fresh water are limited. The problem of water pollution is increasing day by day. Changes in climate and extreme weather patterns, driven by various factors including human, industrial, and commercial activities, as well as natural processes, have led to the contamination of freshwater resources. Wastewater is adversely impacting the lives of individuals. According to UN (United Nation), every year more than 1.5 million people died because of water disease which is much greater than death caused by accidents, crimes and terrorism's combined. To solve this issue, there is a need of bringing out scientific methods that will be used to discover clean water. In order to carry out useful and efficient water quality analysis and predicting the water quality patterns, there are many ANN based methods, different methodologies have been proposed and applied to analyse the monitoring of water quality in various locations. Neural networks, through learning and training processes, acquire the capability to regulate internal system variations, diverging from traditional mathematical equations to establish a robust correlation between input and output. This adaptive approach is particularly adept at addressing nonlinear water environmental challenges. This paper collectively shows and explains some useful water pollution detection techniques using neural network methods from various research results.

2. APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR THE PREDICTION OF WATER QUALITY VARIABLES IN THE NILE DELTA

To select variables for sampling basically depends on the objectives and economics of monitoring. There are several variables that can be chosen from representing surface water quality and so, this issue is highly complicated. There are several methods to select variables like some methods depend on the "water uses as main criterion", some use the level of monitoring (surveillance, intensive control, project oriented) and some applies regression methods to determine the relationship between water quantity and water quality variables.

Many factors regulate water quality like flow rate, contaminant load, medium of transport, water levels etc. Investigating the potentiality of ANNs for modeling the relation between different water quality variables for reducing the variables is the aim of this study [1] specially where monitoring budget is a concern.

2.1 Data

For this study, data are the monthly records of the Oxygen related variables at three monitoring locations of a drainage catchment, in the Eastern Nile Delta of Egypt [1]. Monthly records of 33 parameters, monitored at 102 locations on the Nile Delta drainage system are stored in a National Database operated by the Drainage Research Institute (DRI) since August, 1997. From August 1997 to December 2002, dissolved Oxygen (DO), Biological Oxygen Demand (BOD), and Chemical Oxygen Demand (COD) were measured in those particular locations on monthly basis.

2.2 Method

Different factors may affect ANN modeling. But in this study, only three factors were studied [1].
i. The impact of using different inputs
ii. The impact of the training vs. testing (Tr/Ts) sample sizes and combinations.
iii. The impact of the number of nodes in the hidden layer.
Only one hidden layer is adopted here Based on the fact that one hidden layer is a universal approximator. It was also assumed that only one or two hidden nodes are enough to capture the interrelation between inputs and output in order not to increase the number of parameters of the ANN. After several training trials, the initial weights range is fixed to be around 0.4, the learning rate is fixed at 0.1. training is stopped at the minimum error in the testing data set.
COD (Chemical Oxygen Demand) was chosen as a target output. Three different models have been tested.
i. The first model has BOD (Biological Oxygen Demand model) as a unique input.
ii. The second one has DO (Dissolved Oxygen model) as unique output and
iii. The third one has BOD and DO as a two input model.
Three training and testing combinations were studied, denoted as types A, B, and C. In the first type, first two are used for training and the last one is for testing. In the second type, first one is used for the training and the last two are used for testing. And in the type C, one is used for training and the successive two are used for testing.

In order to evaluate the performance of ANN, two error measures are used to compare the ANNs output with observed values- one is Root Mean Square Error (RMSE) and another is Mean Absolute Relative Error (MARE) [1].

The BRAINCEL (ver. 4) under Excel has been used for the ANN simulations. Total of 54 ANNs models were developed and grouped under 18 different treatments [1].

2.3 Result

From the experiment, it has been ensured that the BOD model and the two-input model under the first combination using one or two nodes in the hidden layer are the best within the 18 developed models [1].

3. FANN-BASED SURFACE WATER QUALITY EVALUATION MODEL AND ITS APPLICATION IN THE SHAOGUAN AREA

A fuzzy neural network model has been proposed [2] to measure the quality of water. This model was applied to measure the quality of water in 16 sections in 9 rivers in Shaouguan area in 2005.

3.1 Data

Water quality data in the Shaoguan area, which is the water source of the Peal River Delta, were chosen for water quality assessment with the proposed fuzzy neural network models. The proposed model has been assessed by 16 sections in 9 rivers in the Shauguan area [2].

3.2 Method

There are two parts of this model [2]. One part is fuzzy mathematics theory which has been used to standardization of samples. And the second part is RBF neural network and the BP neural network which are used to train the sample.

3.2.1 Standardization of fuzzy mathematics. If testing set is composed of n sample and contains m evaluation indicators, and then the testing evaluation matrix is [2]

$$X_{mn} = (X_{ij})_{mn} \quad (1)$$

Here, X_{ij} is the evaluation indicator I of the sample.
The m indicators are measured based on the evaluation standard. Evaluation standard divides the water quality into C category grades. The standar evaluation matrix is:

$$Y_{mc} = (Y_{ih})_{mc} \quad (2)$$

The relative grade of membership of the category is [2]:

$$U_{cn} = (U_{hj})_{cn} \quad (3)$$

3.2.2 Constructing the model with ANNs. After the samples have been standardized with fuzzy theory, the next step is to train the standardized sample. The training outputs were applied to find the relative grade of membership of the category matrix U_{cn} [2]

3.2.2.1 BP Neural Network Model. Two S-shaped transfer functions in a MATLAB neural network toolbox were used in this study [2], the tansig function and logsig function. The accumulated inputs of these functions are then transformed into output of neuron. This outputs are distributed to various connection path ways to provide inputs to other neuron.
The next step in this process is to compute the error of expected output and the real output. If the expected error is not satisfied, the precision, weights and biases are about to be adjusted according to the error.

3.2.2.2 RBF Neural Network Model. With the three layer feed forward structure, the Radial Basis Function (RBF) can be described. The three layers are input layer, output layer and hidden layer. The input layer distributes the input vectors to the hidden layer, it does not process any information. A number of RBF units (n_h) and bias (b_k) comprises the hidden layer. The operation of output layer is linear.

3.2.2.3 Generation of Training sets. According to the surface water environmental standard issued by the government of China, the water quality is divided into 5 grades [2]. Relative grade of membership of standard evaluation indicator matrix used as inputs to train fuzzy neural networks and corresponding relative grade of membership of the category matrix used as target outputs. With the rand function in MATLAB, training samples between all grades of the standard evaluation criteria are generated by the random uniform distribution method. 500 samples are generated between grade 1 and grade 2. 2 000 training samples have been generated. The standard target outputs of the five grades are (1, 0, 0, 0, 0), (0, 1, 0, 0, 0), (0, 0, 1, 0, 0), (0, 0, 0, 1, 0) and (0, 0, 0, 0, 1) respectively. Target outputs of the generated training samples are determined by the corresponding interpolation proportion.

3.2.2.4 Determining Water Quality. By the grade eigen value method, the grade of testing water sample have been determined. The integrated evaluation matrix of the testing set has been given by the formula below [2]:

$H = Grade * U_c n = (1, 2, \ldots c) * U_{cn} = (H_1, H_2, \ldots H_n)$
Where, H_j is the integrated evaluation. Grade=1,2,. . . ,c And U_{cn} is the training output of the testing set.

4. EVALUATION OF THE ABILITY OF AN ARTIFICIAL NEURAL NETWORK MODEL TO ASSESS THE VARIATION OF GROUNDWATER QUALITY IN AN AREA OF BLACKFOOT DISEASE IN TAIWAN

4.1 Data

Wells which are seriously contaminated with groundwater, those have been selected for this study [3] from north to south. Model C has used seasonal data from two seasons. But model A and B used data from only a season.

4.2 Method

4.2.1 Theory of ANN. One of the ANN is BP (Back propagation) ANN, which is self teaching, self organizing and non linear [3]. Generally feed forward neural network consists of three types node- input layer, output layer and hidden layer. Input layers take the inputs and pass it to the hidden layers. Hidden layers process the outputs and pass it to the output layer. The back propagation neural network has two steps of its task. The first step is to feed forward the values, then calculate it. After that, it propagates back it to the earlier stages.

4.2.2 Training of ANN. ANN is trained with some known sets of inputs and outputs []. At the beginning stage, weights are initialized with some random input values. The target of learning is to minimize the error level. While training is being proceeded, the weights are updated according to the predefined training rule.

4.2.3 Evaluation Performance. When the training is complete, the performance is evaluated. The nature of the outcome determines whether the system should be retrained or the system is ok [3]. If the number of hidden layers are too small, then it the system does not have the capability learn the process correctly. If the number of hidden layers is too large, it would take long time and the data could be overfitted. The performance of the training and testing sets are determined by the RMSE (RMSE) [3].

4.3 Technologies

An ANN software package, Qnet 97 is used for this study [3]. Raw data are normalized by transformation. The transformation modified the distribution of the estimated output.

4.4 Result

Among the three models (model A, model B and model C) used here, Model C outperforms than model A and B [3].

5. BACK PROPAGATION NEURAL NETWORK IN THE WATER QUALITY EVALUATION OF QINGDAO DAGU RIVER

The training samples were optimized and the arithmetic, determination of hidden layer nodes amount had also been optimized for improving the NN models performance for this study [4] . Gradient descending arithmetic was added by momentum and self adaptive learning rate was chosen. Pilot calculation arithmetic based on empirical equation optimizes the amount of nodes in networks hidden layer. Random differential in critical value space of grades have been used to train samples to improve model's robustness and veracity of distinguishing.

5.1 Data

As an evaluation object , quality of Dagu river in Qingdao was chosen for this study. There are five cross sections [4] :
1. Ju's village
2. Zhang's village
3. Sand port
4. Jiang' s village
5. Tail sand Bay

The year was divided into 3 periods for water monitored [4].
1. Standard (November)
2. Low (May)
3. High (august)

5.2 Method

The main contents and the operating procedures of water quality evaluation has determined the BP (Back Propagation) network structure [4].

5.2.1 Confirming Input Layer. In this study, the number of input neurons is 7. $DO, COD_{MN}, BOD_5, NH_3 - N, TP, Cr^{6+}$ has been included here as input neurons. They are water quality evaluating indicators [4].

5.2.2 Confirming Output Layer. To evaluate the water quality, five categories have been selected for output layer [4]. They are I, II, III, IV and V. V is the worst category of water. The I, II, III, IV and V categories are indicated respectively by $(1, 0, 0, 0, 0)^T, (0, 1, 0, 0, 0)^T, (0, 0, 1, 0, 0)^T, (0, 0, 0, 1, 0)^T$, and $(0, 0, 0, 0, 1)^T$. Here T represents transposition [4].

5.2.3 Confirming Hidden Layer. The method for estimating hidden layer is:

$$n_y = mn_z/(n_x + n_z) \tag{4}$$

The model error and the accuracy of water quality evaluation were the target function to confirm the number of hidden nodes in network model in this study.

5.2.4 Selection of Learning Algorithm. For accelerating network training process, gradient descent method containing momentum and self adaptive learning rate has been selected for this study [4].

5.2.5 Selection of Learning Sample. Water quality assessment is an issue of pattern recognition. In this study, random differential algorithm has been used to train sample [4].

5.3 Result

The water quality in Laixi region of Dagu river's Qingdao segment was assessed, using the established model. The assessment acquired stable and reliable assessment results [4].

6. APPLICATION OF RAGABP ANN BASED ON AM-MCMC IN WATER QUALITY EVALUATION

Back Propagation Artificial Neural Net based on "Real coded Accelerating Genetic Algorithm" and "Markov Chain Monte Carlo" is based on Adaptive Metropolis which was used to measure water quality [5]. RAGA was used to optimize topology, initialize weights and bias of BP [5]. MCMC was adopted to produce enough simulated samples for training BP net and to consider fuzziness between adjacent grades of water quality. Adaptive Metropolis method has been used as a sampling method to improve sampling efficiency of MCMC. Results of study cases show RAGABP based on AM-MCMC improve convergence velocity more 20% than standard BP, and evaluation results of RAGABP are more objective, reasonable than that of single indicator method [5].

6.1 Data

6.1.1 Case 1. Monitoring data are available on four sites in Raohe irrigation area in northern of Raohe country in Heilongjiang province (shown in table1) [5]. RAGABP based on MCMC was applied to measure the water quality of every site in this case. The standard of water quality was chosen as the standard of surface water quality shown in table 2 [5]. The observed water quality of this area is shown in table 1 [5].

6.1.2 Case 2. The observation data of water quality of the 290 irrigation areas (lies on the joined area of Songhuajiang river and Heilongjiang river) are available at eight monitoring sites

6.2 Method

6.2.1 RAGABP. BP (Back Propagation of error) of ANN adjusts its weights and bias by back propagation in energy function in net. The convergence velocity of training of standard BP ANN was slow and even failed training [5]. So, the Real Coded Accelerating Genetic Algorithm (RAGA) has been used to optimize topology, initial weights and bias of ANN in this paper [5].

6.2.2 AM-MCMC. Markov Chain (MC) was introduced to improve the convergence velocity of Monte Carlo simulation into study of parameters uncertainty. As AM is used for multi-dimension vector as well as its sampling efficiency is higher, it needn't specify a transfer distribution.
The sampling steps of AM are showed below:

i Initialization : i=0
  - a Calculation of c_i: c_i=c_0, if $i \leq 0$ Otherwise c_i=s_d(Cov($q^0, q^1, \ldots, q^{t-1}$))+$s_d \varepsilon I_d$
  - b Production of Candidate Variable: $q \simeq N(q_i, c_i)$
  - c Calculation of received probability: $\alpha(q_i, q^*) = min\{1, \pi(q**)/\pi(q_i)\}$
  - d Production of a random number: $u \simeq U(0,1)$
  - e If $u < \alpha$, then $q_{i+1} = q^*$, else $q_{i+1} = q_i$

ii Getting an initial state q_i from a prior interval of variable q.

iii $I = i + 1$, perform $a \simeq e$, till enough samples are gotten.

Table 1. Observation Of Water Quality In RAOHE [5]

	Monitor Site			
Indicator	1	2	3	4
DO	8.69	8.61	16.41	3.5
COD	4.477	6.086	15.255	3.422
BOD	1.69	2.03	5.35	0.81
$NH_3 - N$	0.12	0.314	0.1	0.14
P	0.4	0.482	0.5	0.2
AS	0.007	0.007	0.1	0.015
Cr^+	0.00019	0.0001	0.002	0.0025
Pb	0.023	0.001	0.001	0.032

Table 2. Standard Of Water Quality (BG3838-2002) [5]

Indicator	I	II	III	IV	V
DO≥	7.5	6	5	3	2
COD_Mn≤	2	4	6	10	15
BOD_5≤	3	3	4	6	10
$NH_3 - N$≤	0.15	0.5	1.0	1.5	2.0
P≤	0.02	0.1	0.2	0.3	0.4
As≤	0.05	0.05	0.05	0.10	0.10
Cr^{+6}≤	0.01	0.05	0.05	0.05	0.1
Pb≤	0.01	0.01	0.05	0.05	0.1

6.2.3 RAGABP Based On MCMC. MCMC was introduced to BP model to simulate values of indicators in all grades. MCMC can consider historic information of samples and randomicity of indicator values. RAGABP based on MCMC can produce samples as many as expectation.

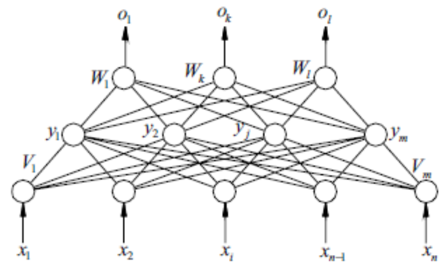

Fig. 1. Three Layer BP Artificial Neural Network [5]

6.3 Result & Evaluation

Table 3, table 4 and table 6 represents the evaluation of water quality using the proposed method.

7. ANN BASED ON PSO FOR SURFACE WATER QUALITY EVALUATION MODEL AND ITS APPLICATION

In this study [6], A BP neural network model has been proposed to evaluate water quality and here the BP neural network model has been trained using PSO (Particle Swarm Optimization). For this study, the current condition and changing trend of surface water in Suzhou city has been analyzed. The hidden layer choice has been also optimized. This model has been used to evaluate the water of

Table 3. Output Error of Test Samples for RAGABP [5]

Grade	I	II	III	IV	V
Error	0.02	0.05	0.04	0.06	0.03

Table 4. Evaluation Of Water Quality In Raohe (Output of RAGABP) [5]

Sites	I	II	III	IV	V
1	0.00	0.00	0.00	0.00	0.991
2	0.00	0.00	0.00	0.00	1.01
3	0.00	1.03	0.00	0.00	0.00
4	0.00	0.00	0.00	0.10	0.99

Table 5. Observation Of Water Quality In 290 areas of Songhuajiang river and Heilongjiang river. (MG/L) [5]

Site	1	2	3	4	5	6	7	8
$DO \geq$	7.87	7.93	7.794	5.97	7.82	7.64	7.88	7.56
$COD_Mn \leq$	1.68	2.16	2.62	4.23	3.67	3.33	2.31	3.74
$BOD_5 \leq$	13.66	9.14	120.35	46.86	120.27	158.75	89.95	60.21
$NH_3 - N \leq$	0.32	0.42	0.65	1.02	0.89	0.23	0.75	0.97
$P \leq$	0.06	0.05	0.70	1.10	0.73	1.06	0.95	0.74
$As \leq$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$Cr^{+6} \leq$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$Pb \leq$	0.02	0.02	0.04	0.01	0.02	0.03	0.02	0.02

Suzhou city. Then the result has been compared with the BP model without training PSO and also with the reported result.

7.1 Data

This method has been applied on surface water collected from Suzhou city. The surface water quality of Suzhou City is presented in table 7 [6]. Figure 3 presents a sample graphical view of different indicators performance in measuring water quality.

7.2 Method

7.2.1 BP Neural Network Model. The neural network with multi hierarchy structure has been used, that is based on BP neural network. This is the most used neural network model used in hydrology modeling which has also been used in this study.
Three layers (input layer, hidden layer and output layer) of BP neural network has been used here. In the hidden and output layers, the net input to unit I is of the form:
$s_i = \sum w_{ij} y_i + \theta_i$
Several types of transfer functions have been used here. The most used transfer function is sigmoid function as it is differentiable everywhere and monotonically increasing. Two S-shaped transfer function of MATLAV neural network toolbox have been used here. The two used functions are tansing function and logsig function. The functions are of the following form:
$\tan sig(n) = 2/1 + e^{-2n} - 1$
$\tan sig(n) = 1/1 + e^{-n}$
Inputs are accumulated by these and then transformed to the neuron output.

7.2.2 PSO Algorithm. Particle Swarm Optimization (PSO) is a an iterative optimization algorithm and a kind of evolutionary computation. This is kind of similar to the genetic algorithm. The idea of PSO is simple. PSO is initialized with the best fitted value as far as achieved. Then it searches for better fitness than the initialized value. If it gets a new value, it calculates the fitness. If the fitness is better than the previous one, then it updates the new best value otherwise discard the value (if it is not better than the previous).
When the optimization are found, the particles update themselves to fin their own velocity and location.
$v = v + c_1 \times rand() \times (pbest - present) + c_2 \times rand() \times (gbest - present)$
$Present = present + v$

7.2.3 Generation of Training Sets. The water quality has been divided into five grades (grade- I, II, III, IV and V). Surface BP neural networks have been trained with the grade of standard evaluation indicator matrix has been used as input and the grade of category matrix has been used as target outputs to train BP neural networks.

Table 6. Evaluation Of Water Quality In 290 areas of Songhuajiang river and Heilongjiang river. (Output of RAGABP) [5]

Sites	I	II	III	IV	V
1	0.00	1.01	0.01	0.00	0.00
2	0.00	1.00	0.00	0.00	0.00
3	0.00	0.00	0.02	0.99	0.01
4	0.00	0.00	0.01	1.00	0.00
5	0.00	0.00	0.00	1.00	0.01
6	0.00	0.00	1.00	0.00	0.00
7	0.00	0.01	1.01	0.01	0.00
8	0.00	0.00	0.98	0.00	0.00

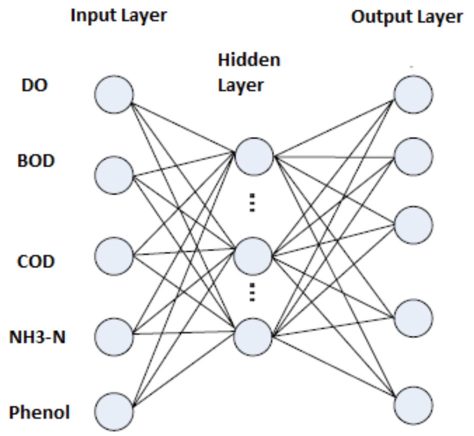

Fig. 2. structure of BP neural network of water quality evaluation [6]

7.3 Evaluation & Result

The water quality on the 20 monitoring sections in Suzhou River has been evaluated according to the BP network test. The result is presented in the table 8 [6] and table 9 [6].

Table 7. Surface Water Environmental Quality Standard MG/L [6]

Indicator	I	II	III	IV	V
DO	> 7.5	6.0	5.0	3.0	< 2.0
BOD	< 3.0	3.0	4.0	6.0	10.0
COD	< 15.0	15.0	20.0	30.0	40.0
$NH_3 - N$	< 0.015	0.5	1.0	1.5	2.0
Phenol	0.0002	0.0002	0.0005	0.01	0.1

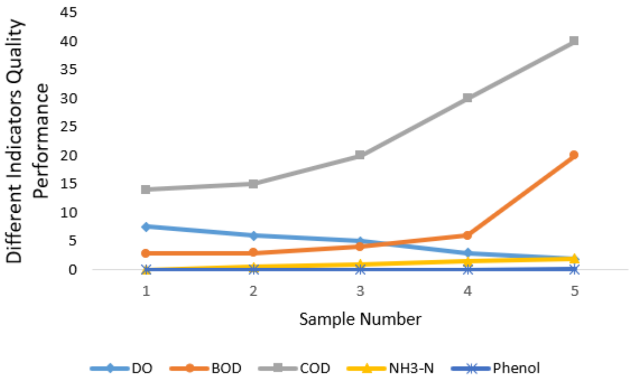

Fig. 3. A sample of Surface Water Environmental Quality Standard MG/L [6] from the total Evaluation [6]

Table 8. Performance Comparison In Different Topology Of BP Neural Network [6]

BP Neural Network	Topology	Epochs	MSE
BP I	5-7-5	545	0.0000997887
BP II	5-8-5	356	0.0000993658
BP III	5-9-5	654	0.0000998447
BP IV	5-10-5	605	0.0000994926
BP V	5-11-5	546	0.000099837

8. APPLICATION OF ARTIFICIAL NEURAL NETWORK IN URBAN LANDSCAPE WATER QUALITY EVALUATION

In this study [7], BP neural network has been used to evaluate the landscape water quality. An optimization technique of BP neural network has been also provided here, which mainly uses MATLAB programming. Based on the sampling and monitoring water quality in a continuous basis, artificial neural network has been used here to build a model for landscape water evaluation in a quick manner.

8.1 Data

8.1.1 Selection of Sampling Locations for Collecting Data. Data has been collected from six sampling locations of water. The locations were selected based on research survey and the layout principle of sampling according to the need of this study. The selected sampling locations are provided below:

—**Location 1**: Location 1 is selected on the outlet section of the rainfall pumping station.
—**Location 2**: Location 2 is selected near an industrial outfall.
—**Location 3 and 4**: Location 3 and 4 are selected close to each other, in order to study the role of aquatic plants on the degradability of pollutants.

Table 9. Performance Comparison In Different Topology Of BP Neural Network [6]

Section	Output of BP Neural Network	Rank
1	0.0950, 0.0712, -0.2156, 1.1358, 0.4913	IV
2	0.1051, 0.1018, -0.6987, 1.1706, 0.6158	IV
3	0.1051, 0.1018, -0.6987, 1.1706, 0.6158	IV
4	0.0289, 0.4439, -1.1277, 1.2727, 0.7148	V
5	0.0895, 0.2479, -0.7020, 1.1468, 0.6055	IV
6	(0.8328, -0.4097, 0.2162, 0.5021, -0.1318)	I
7	(0.8999, -0.5292, 0.2330, 0.4255, -0.2703)	I
8	(0.5002, -0.2298, -0.1649, 0.9345, 0.0737)	IV
9	(0.1302, 0.2149, -0.7503, 1.12505, 0.6320)	IV
10	(0.0049, 0.2377, -0.7802, 1.2505, 0.6320)	IV
11	(0.1171, 0.1933, -0.7997, 1.3874, 0.5165)	IV
12	(0.1050, 0.1378, -0.6978, 1.1497, 0.4861)	IV
13	(-0.0745, 0.1554, -0.6453, 1.1539, 0.6508)	V
14	(-0.0027, 0.2885, -0.8473, 1.2380, 0.6673)	IV
15	(0.2405, -0.0411, -0.1430, 0.8883, 0.3079)	IV
16	(0.2476, -0.1492, -0.1430, 0.8883, 0.3079)	IV
17	(0.9855, -0.2645, 0.6962, -0.0252, -0.9057)	I
18	(0.2426, 0.0296, -0.5274, 1.0213, 0.3644)	IV
19	(0.6592, -0.3713, 0.0866, 0.8443, -0.0942)	IV
20	(0.3026, 0.4944, -1.2283, 0.9277, 0.2788)	IV

Table 10. Average Monitoring Results Of The Landscape River Water Quality In July 2008 (mg/L) [7]

Location	COD_{cr}	TP	TN	$NH_3 - N$	Chloride	DO
1	79.16	1.03	5.29	4.38	417.8	5.12
2	63.83	0.57	4.49	3.05	382.7	5.94
3	59.58	0.51	3.44	2.60	374.3	5.72
4	61.51	0.56	3.59	2.80	353.2	6.36
5	34.76	0.09	3.73	2.66	229.1	5.66
6	40.40	0.04	2.99	2.71	184.8	5.86

—**Location 5 and 6**: Location 5 and 6 are selected on the downstream river.

8.1.2 Analysis and Monitoring Water Quality Indexes. Eight water quality indexes including water temperature, pH, dissolved oxygen (DO), total nitrogen, ammonia nitrogen, total phosphorus, chemical oxygen demand (COD) and chloride are monitored for this study. Table 10 [7] shows the monitoring data.

8.2 Method

8.2.1 Specify Evaluation Criteria and Determination of the Evaluation Indexes. Based on “National Surface Water Environmental Quality” the standard

8.2.2 Establishing The Model. BP neural network model is the most used neural network model. It is a feed forward neural network having one input layer, one or more hidden layers and one output layer. There exists a non linear relationship between each input layer and output layer in each neuron, except for each the input layers. The following S function is the most used and it has been used in this paper:

$$f(x) = 1/1 - exp(-(x + \theta_i)/\theta_0)$$

The Back propagation consists of positive propagation and back propagation. Through repeating these propagations, neurons weights are adjusted until there is not any chance to reduce more.

Table 11. Evaluation Criteria Of Landscape Water Pollution Degree Table Type Styles [7]

Index	$NH_3 - N$	TN	COD_{cr}	TP
I	0.15	0.2	15	0.02
II	0.5	0.5	15	0.1
III	1.0	1.0	20	0.2
IV	1.5	1.5	30	0.3
V	2.0	2.0	40	0.4

Table 12. Expectation Output Of Output Layer Node [7]

I	II	III	IV	V
1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

The calculation steps of BP network are represented below:

i Initialization of network weights
ii Training of data set
iii Calculation of error value of each node of output layer (for S function)
iv Calculation of error value of each node for previous layer
v Adaption of weight and threshold value
vi Calculation of error function value until it reaches predetermined minimum error value
vii Savings of weights and thresholds derived from training to process input and output of predicted sample

A BP neural network structure is shown in 4

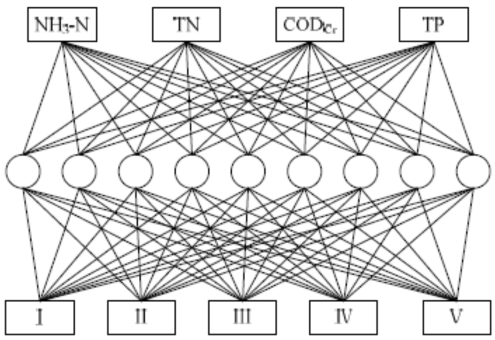

Fig. 4. Neural network structure diagram of landscape water quality evaluation [7]

8.2.3 Network Training. Five grading standards for water quality evaluation has been represented in Table 11 [7] as training samples, the five nodes desired outputs of the corresponding output layer has been represented in Table 12 [7].
BP neural network stops learning and save the weights and thresholds which are derived from their training. Standard sample output is shown in Table 13 [7].

Table 13. Standard Sample Output [7]

I	II	III	IV	V
0.9985	0.0008	0.0033	0.0030	0.0026
0.0009	1.0018	0.0002	0.0078	0.0007
0.0001	0.0008	0.9965	0.0063	0.0009
0.0010	0.0010	0.0043	0.9960	0.0029
0.0006	0.0008	0.0014	0.0021	0.9986

Table 14. Water Quality Evaluation Network Results of Landscape [7]

Location	I	II	III	IV	V	Control Level
1	0.0613	0.0913	0.0680	0.0549	1.4548	V
2	0.0347	0.0397	0.1409	0.0842	1.4498	V
3	0.0240	0.0516	0.1265	0.0784	1.3640	V
4	0.0232	0.0752	0.0937	0.0652	1.3737	V
5	0.1124	0.1038	0.0460	0.0459	1.1318	V
6	0.1167	0.0153	0.1772	0.0417	1.0703	V

8.3 Technology

MATLAB programming has been used for this study. MATLAB toolbox provides a function of BP network and with that it is possible to avoid complicated mathematical calculation and difficult code editor to build the targeted model.

8.4 Evaluation & Result

Taking the average of the monitoring COD, ammonia nitrogen, total nitrogen and total phosphorus at the six sampling locations of the landscape river (shown in Table 10) which are used here as model input variables, evaluation results are shown in Table 14.
From the result shown in table 14, it has been understood that the landscape water generally does not reach the standard quality according to the natural water quality standard and generally landscape water quality is at the Grade V standard. The quality of water gradually improves according to the flow direction of river.

9. CONCLUSION

Water pollution problems have become severe and now these problems are not limited to a particular region, these problems have become a global issue. In order to use and protect water resources, it is necessary to evaluate water quality, detect water pollution and manage ways to reserve enough water for daily use. There are many methods to evaluate water quality. But among various methods artificial neural network methods are faster and more effective than other methods. Artificial neural network methods are highly non linear mapping, it can learn mapping among large number of models. In this paper, we have presented various “Artificial Neural Network” method based water quality evaluation methods which have already been applied in various water resources (ground water, rain water, river water etc) of various regions. Among those methods, BP artificial neural network method has been widely used though it has some drawbacks.This method provides better performance than other available methods of ANN for water quality evaluation. Likewise BP method, fuzzy neural network method, RAGA BP method based on AM-MCMC, uncertainly mathematical model, RBF neural network method etc are also common methods for water quality evaluation. For the healthy development of lives in the world, pure water is one of the basic requirements and for this reason effective water quality evaluation methods should be quickly developed. Based on the effective evaluation methods, it is possible to avoid polluted water from being used to prevent various water diseases as well as to prevent other problems caused by polluted water.

10. REFERENCES

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