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Determination of water quality parameters and nutrient level with an Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

In this research, the physico-chemical water quality parameters and the effect of climate changes on water quality is evaluated. During the observation period (5 months) physico-chemical parameters such as water temperature, turbidity, saturated oxygen, dissolved oxygen, pH, chlorophyll-a, salinity, conductivity, and concentration of total nitrogen (nutrient level) as main pollutant factor have been measured in Iran from September to February 2013 in the Amirkabir dam area. Moreover, an adaptive neuro fuzzy inference mechanism (ANFIS) is designed for the sake of modeling and prediction. In order to learn the proposed ANFIS mechanism a Quantum behave particle swarm optimization (QPSO) is employed. The proposed ANFIS architecture has nine-input and one output in which the physico -chemical parameters of water and total nitrogen have been considered as input and output of the proposed ANFIS, respectively. In this paper to reduce the noise and measurement errors a wavelet transform strategy is utilized.

Keywords: Water quality; Nutrient level; Physico-chemical parameters; ANFIS; Wavelet

INTRODUCTION

Nowadays, the existence of a correlation between the environment and human`s health shows that the determination of the environmental species is important. Measurement of Natural water parameters have become more important than before because of to rising environmental problems and desire for less energy consumption [1]. In several countries new environmental regulations have been developed for decreasing the different sources of pollution, and improving the quality of water [2]. Because the concentration of phosphorous and specially nitrogen as nutrient parameters are considered as main sources of pollution, determination of different anions are recognized as the most important parameters to characterize the quality of water. These parameters from in-situ analysis have been applied in natural water more than the bench scale analysis [3]. High levels of nitrate are toxic for human body. The determination of total nitrogen is the main step in the potentially polluted waters. There are different analytical methods for nitrate analysis such as UV detection and titrations [4]. The pH value

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of water could be affected by increasing of nutrient parameters [5]. Many statistical models can be applied to predict the changes of different parameters in water quality [6]. [7] developed linear statistical models, also [8] presented a similar approach based on pisson regression. Many statistical models which have been developed are not accurate enough for computations [9-12]. [13] and [14] presented traditional statistical methods. [15] applied a neural- network system for modeling of water's physico-chemical parameters.. Among different models, adaptive neuro fuzzy inference system (ANFIS) [16] can be considered as an advanced mathematical tool in the modeling of non-linear data including different water quality forecasting. The ANFIS method as an advanced mathematical strategy has been utilized by many authors for different application in science [17]. Different strategies have been investigated to train the ANFIS parameters [18]. In this paper, for high precision modeling a Quantum behaved particle swarm optimization (QPSO) algorithm is presented to train the ANFIS parameters. It is noted that the first purpose of this research is determination of different physico- chemical parameters and nutrient level in different depth of Karaj dam. Moreover, modeling with a powerful approach based on the ANFIS mechanism for modeling these parameters is the second goal of this article. After construction and validation the ANFIS model for the collected data, this model is used for the prediction of water nutrient level.

EXPERIMENTAL

Site description

Amirkabir dam located in the 63 km of north western of Tehran, Iran has been examined in this study. The physico-chemical parameters and nutrient loads flowing in to the repository have been investigated. Detailed sampling of the water has collected from September to February 2013.

Sampling and laboratory analysis

Water samples have collected monthly at 5 stations located in Amirkabir dam in different depths from 1 to 75 meters from the surface to the bottom. Physical and chemical factors such as water temperature $\left({}^{\circ}C\right)$, saturated oxygen $(Os\%)$, dissolved oxygen$\left(\mathrm{Od, ppm}\right)$, pH, chlorophyll-a $\left(mg/l\right)$, salinity$\left(psu\right)$, turbidity $\left(NTU\right)$ and conductivity(μZ) and total nitrogen $\left(\mathrm{TN, mg/l}\right)$ in different depths have been determined (Table.1). The performances of the laboratory-scale have been determined for each month. Among all factors of water such as temperature, saturated oxygen, dissolved oxygen, pH, chlorophyll-a, turbidity and salinity have been measured in-situ by using of *CTD* (Current, Temperature, and Depth) model: OCEAN SEVEN 316, IDRONAUT. During in-situ measurements, the sound recorded the depth of water. Then averaged of recorded data are evaluated. The samples are collected at Niskin water sampler in the morning hours between 9-11 am. A few numbers of samples are removed from the sampler and transferred for laboratory analysis in the polyethylene bottle. It has kept in to a cool and dark container and transported to the laboratory for nitrogen measurement. The experimental results of this determination process are repeated for each sample, three times. Al samples are filtered through a Whatman No 40 filter (0.45 µm) to remove any suspended solids and the filtrates are stored in dark bottles at 4 °C. Nitrate is determined by 2, 6-dimethyl phenol method [19] and also with ion chromatography [20], nitrite by the reaction of NO_2^- ions with sulphanylamyd yielding colored diazonium salts, intensively [21].

Adaptive Neuro Fuzzy Inference System (ANFIS)

In this section an ANFIS mechanism is designed for the sake of the modeling and prediction. The proposed strategy is depicted in Fig.1 in which five main steps have been considered to achieve a high accuracy of modeling. The architecture diagram of the neuro-fuzzy inference mechanism is depicted in Fig.2

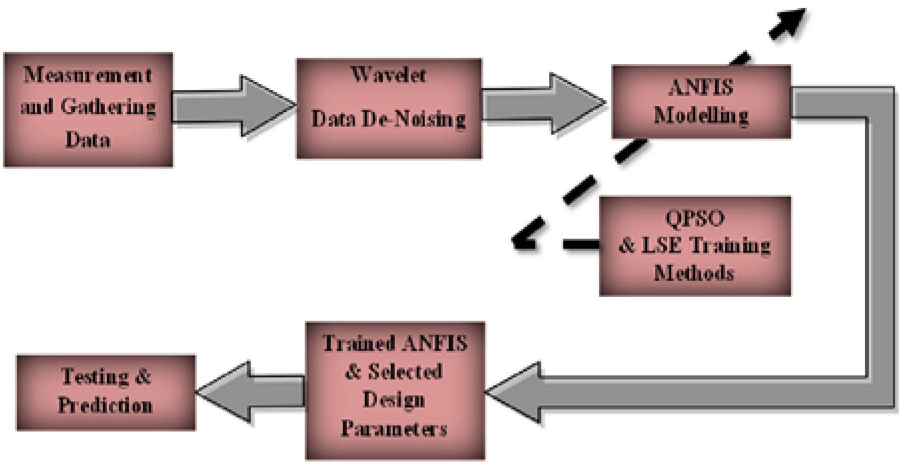

Fig.1. Block diagram of the proposed method to predict the water quality parameters and nutrient level.

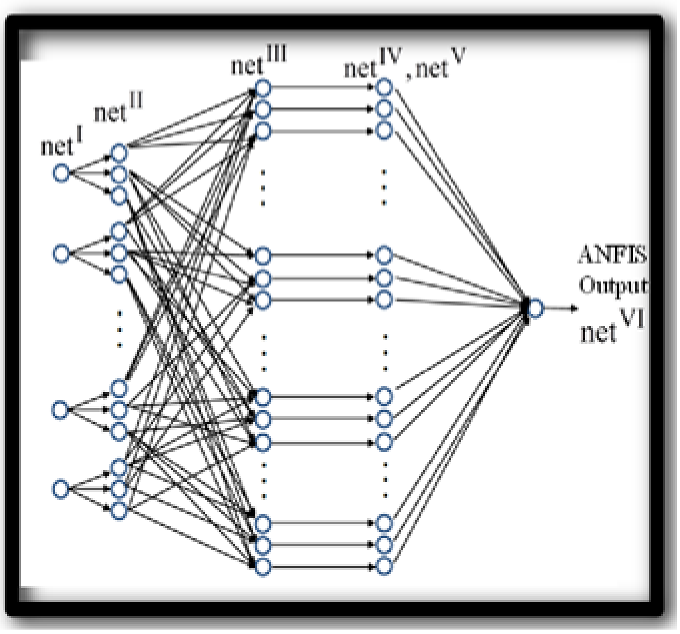

Fig.2. The architecture diagram of neuro-fuzzy inference mechanism.

Description of ANFIS: In the proposed ANFIS mechanism, the four main layers NN is used (Fig. 2). These layers represent the inputs to the network, the membership functions, the fuzzy rule base and the outputs of the network, respectively.

Layer I: input layer

Inputs and outputs of nodes in this layer are represented as

$$net_i^1 = x_i, y_i^1 = f_i^1(net_i^1) = net_i^1 = x_i, \quad i = 1,...,9 \qquad (1)$$

where x_i and y_i^1 are the input to the first layer and outputs of the input layer, respectively. In this layer, the weights are unity and fixed.

Layer II: membership layer

In this layer, each node performs a fuzzy set and the bell function is adopted as a membership function

$$net_{i,j}^{II} = \frac{1}{1+\left|\frac{x_{i,j}^{II}-c_j^{II}}{b_j^{II}}\right|^{2d_j^{II}}}, \quad y_{i,j}^{II} = f_{i,j}^{II}(net_{i,j}^{II}, c_j^{II}, b_j^{II}, d_j^{II}) \qquad (2)$$

where c_j^{II}, b_j^{II} and d_j^{II} are the bell function parameters which is estimated by alearning methodology. The variable $x_{i,j}^{II}$ is the output of layer I.

Layer III: rule layer

This layer includes the rule base used in the fuzzy logic control. Each node in this layer multiplies the input signals and outputs the result of product

$$net_{i,jk}^{III} = (x_{i,j}^{III} \times x_{i,k}^{III}), \quad y_{i,j}^{III} = f_{i,j}^{III}(net_{i,jk}^{III}) \qquad (3)$$

here $x_{i,j}^{III}$ is the output of layer II. The values of link weights between the membership layer and rule base layer are unity.

Layer IV: the ratio of the firing strength of the rule

The i-th node of this layer calculates the ratio of the firing strength of the i-th rule to the sum of all the firing strength:

$$net_{i,j}^{IV} = \frac{net_{i,jk}^{III}}{\sum_{i=1}^{Nr} net_{i,jk}^{III}}, \quad y_{i,j}^{IV} = f_{i,j}^{IV}(net_{i,j}^{IV}) \qquad (4)$$

Layer V: Sugeno Consequence

In this layer node i has the following node function

$$net_{i,j}^{V} = net_{i,j}^{IV} f_{i,j}^{V} = net_{i,j}^{IV}\left(\sum_{i=1}^{Nr-1} p_{ij}x_i + r_{ij}\right) \qquad (5)$$

Layer VI: overall output

The single node in this layer computes the overall output as the summation of all incoming signals

$$net_{i,j}^{VI} = \sum_{i=1}^{Nr} net_{i,j}^{V} = \frac{\sum_{i=1}^{Nr} net_{i,jk}^{III} f_{i,j}^{V}}{\sum_{i=1}^{Nr} net_{i,jk}^{III}} \qquad (6)$$

It is noted that the least square method with singular value decomposition (SVD) has been utilized to learning the consequence parameters and QPSO algorithm which is obtained in the next section is employed to learning the antecedents or bell function design parameters.

Quantum computing is a new theory which has emerged as a result of merging computer science and quantum mechanics. Its main goal is to investigate all the possibilities if it followed the laws of quantum mechanics. During the last decade, quantum computing has attracted widespread interest and has induced intensive investigations and researches, since it appears more powerful rather than its classical counterpart. Indeed, the parallelism that the quantum computing provides reduces obviously the algorithmic complexity. Such an ability of parallel processing can be used to solve the combinatorial optimization problems which require the exploration of large solutions spaces. In the classical PSO, a particle is stated by its position vector x_{ij}^{t} and velocity vector v_{ij}^{t}, which determine the trajectory of the particle. The particle moves along a determined trajectory following Newtonian mechanics. However if we consider quantum mechanics, then the term trajectory is meaningless, because x_{ij}^{t} and v_{ij}^{t} of a particle cannot be determined simultaneously according to uncertainty principle. Therefore, if individual particles in a PSO system have quantum behaviour, the performance of PSO will be far from that of classical PSO [22]. In this section the basic iterative equations of the QPSO is considered by the following form

$$x_{ij}^{t+1} = P_{ij}^{t} + \beta |mbest - x_{ij}^{t}| \ln(1/u) \quad if \quad k \geq 0.5 \tag{7}$$

$$x_{ij}^{t+1} = P_{ij}^{t} - \beta |mbest - x_{ij}^{t}| \ln(1/u) \quad if \quad k < 0.5 \tag{8}$$

Where

$$P_{ij}^{t} = (p_{ij}^{t} c_1 + c_2 p_{gj}^{t}) / (c_1 + c_2) \tag{9}$$

$$mbest = \frac{1}{M}\sum_{i=1}^{M} P_i = \left(\frac{1}{M}\sum_{i=1}^{M} P_{i1}, \frac{1}{M}\sum_{i=1}^{M} P_{i2}, \ldots, \frac{1}{M}\sum_{i=1}^{n} P_{ij} \right) \tag{10}$$

Mean best ($mbest$) of the population is defined as the mean of the best positions of all particles. The parameters u, k, c_1 and c_2 of equations (7), (8) and (9) are uniformly distributed random numbers in the interval [0, 1] and the parameter β is called contraction-expansion coefficient.

In the proposed strategy, the wavelet de-noising method is employed to reduce the noise due to measurement instrumentation error [23-26]. Therefore, more accuracy of the proposed ANFIS can be obtained. In the next section the performance of the proposed modeling strategy is presented by some simulation results.

RESULTS AND DISCUSSION

Seasonal scale variations have played an important role in regulating water quality. It is noted that the climate changes is likely to result of the changes in water quality because it can be affected on the precipitation and temperature of aquatic process.

The water temperature have been observed at measurement stations with maximum values of 24 °C in the surface and 6.0°C in the 75 meters below the surface in autumn. The diagrams of temperature and salinity (Fig.6) are shown two stratifications occurred in the water column height during the September – February. The diagram of temperature consists of a surface stratification at a depth of between 3 to 6 meters. The next one is depth of stratification which started at depth of 65 meters and finished at depth of 75 meters. During this period, diagrams of turbidity and conductivity also show a surface stratification at a depth of 4-7 meters and a depth stratification of about 67 meters to 73 meters (Fig.7). Despite Precipitation, pH did not increase or decrease through the period of record from (6.3 -7.5). The results of this study demonstrate the concentrations of Nitrogen in different depths can be reached 1.94 mgL^{-1} in the surface 0.06 mgL^{-1} the 75 meters below from the surface in the autumn until middle of winter. There are several pollution sources that impacted the water quality in the rivers and dams. The saturated oxygen in fresh waters would be inversely proportional with the temperature of water as well as pressure effects and the DO concentration. The solubility of gases in a volume of liquid is proportional with the pressure of the exerting gas. Salinity also decreases the DO saturation value. Nitrogen concentration in most fresh water bodies shows an increasing trend in autumn. Previous investigation has shown that there is a close correlation between turbidity and pollution of water in summer. Therefore, we have to develop several predictive models which can explain water quality as a function of climate and also the source of pollution. One of the goals of this research is to find the correlation between physico-chemical parameters and nutrient level.

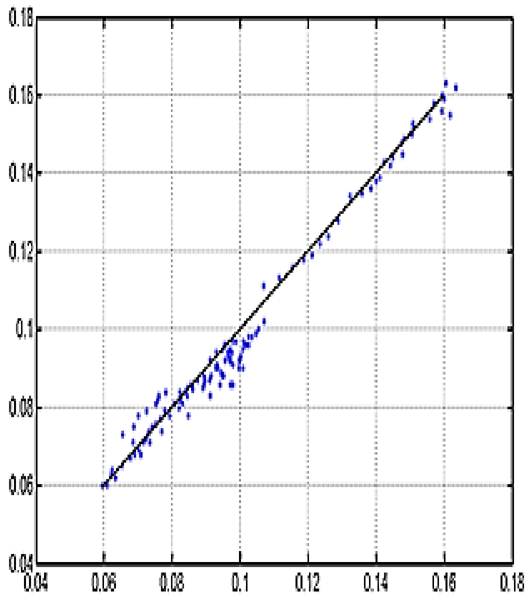

Fig. 3. Scatter plot of all data include test and train.

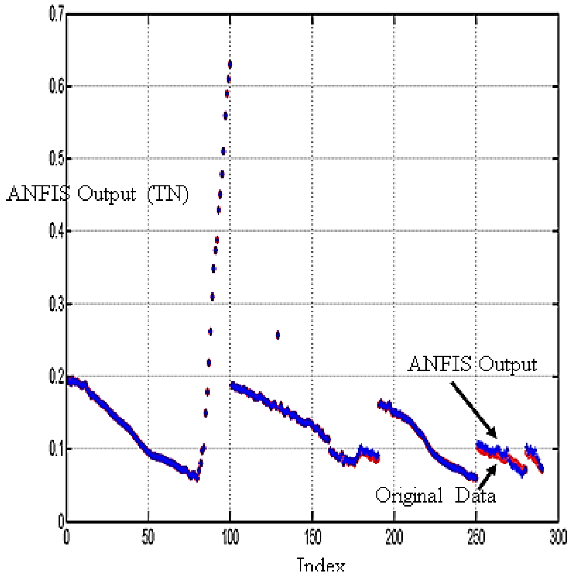

Fig.4. Performances of the discontinue model (Train and Test).

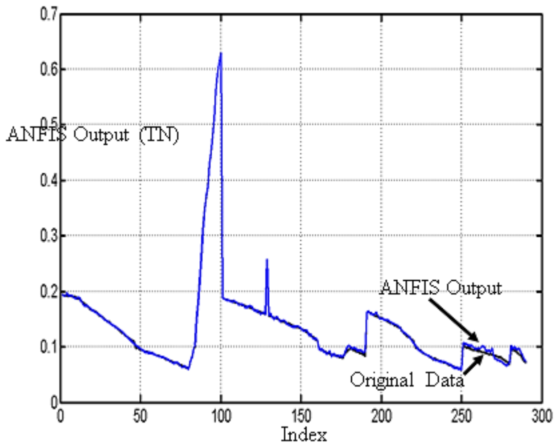

Fig. 5. Performances of the continue model (Train and Test).

The ANFIS results show that the nutrient level is more strongly correlated with physico-chemical parameters. In the simulation and modeling process 200 populations and 200 generation are chosen in the QPSO algorithm. 3 rules for each ANFIS input from fuzzy layer are considered. The propose ANFIS architecture has 9 input and one output as demonstrate in Fig 2. Fig. 3 shows the scatter plot of the train and test data. The superiorly of the proposed method can be easily understood from the Figs. 4 and 5 for continues and discontinues validating between original and predicted data. 170 data from 290 data have been considered for the ANFIS training. Fig. 6 shows the fitting accuracy for each generation. The root mean square error (RMSE) is 0.1775 percent and absolute average error is 0.2093. These results show the level of accuracy of the proposed modeling and prediction strategy. The developed model has been used to under different conditions. Several model runs have been performed in order to produce well established parameterization for physic chemical parameters and nutrification of water properties. Our data show a statistically significant correlation between physic chemical parameters and nutrient level and along with the results a strong modeling method is suggested.

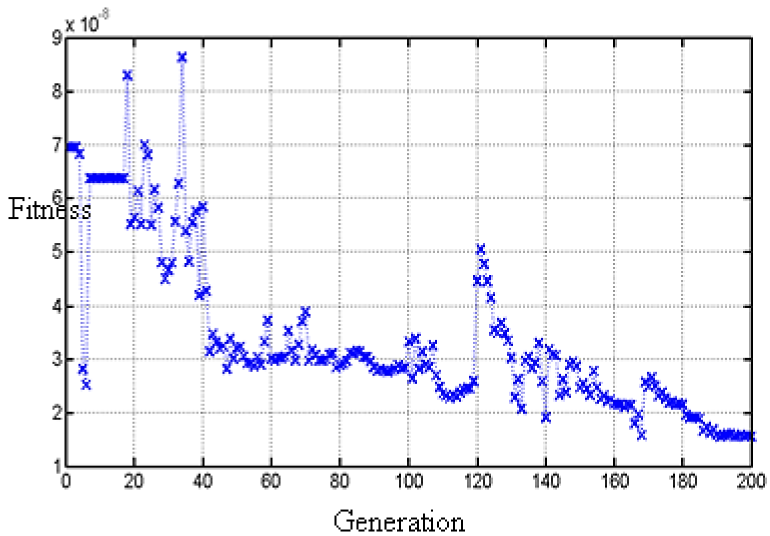

Fig. 6. Evaluation during the generation.

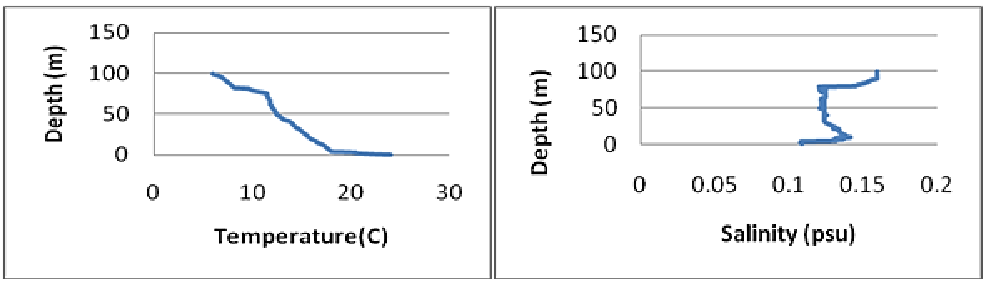

Fig. 7. the diagram of temperature and salinity.

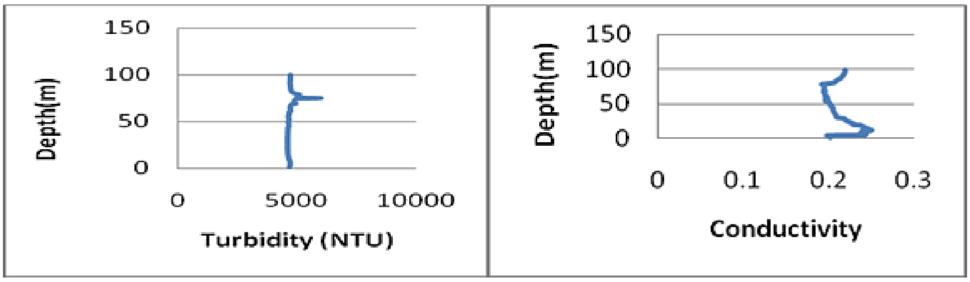

Fig. 8. The diagram of conductivity and turbidity.

Table 1. The characteristics of the water data in different level stations

Parameters	Maximum	Minimum	Average
Input			
Depth (m)	75	0	37.5
Water temperature (°C)	24.0	6.0	15.0
Turbidity (NTU)	5400	3150	4275
Saturated oxygen (%)	159	53.0	106
Dissolved oxygen (ppm)	14.5	6.16	10.33
pH	7.55	6.3	7.02
Chlorophyll-a (mg/lit)	1090	628	859
Salinity (psu)	0.158	0.108	0.133
Conductivity (µs/cm)	0.272	0.190	0.231
Output			
Total nitrogen (mg/lit)	1.94	0.06	1.00

Our results strongly suggest that future work is needed to verify the roles of turbidity inquality and further to assess how such roles might impact the fate of other contaminants in aquatic systems.

CONCLUSION

This study shows that the proposed ANFIS mechanism could be successfully applied to prediction of correlation between physico-chemical parameters and nutrient level in water. In this paper, the model evaluation shows that the absolute average error is negligible than the other results from previous work. Because of measurements errors, the wavelet de-noising as a mathematical tool has been applied to remove the produced noise result of measurement errors.

Finally, nutrient level modeling has been done, perfectly and the proposed strategy is accurate enough to predict the nutrient level in the area of dam.

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