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# Analysis Water Quality by Artificial Neural Network in Bazoft River (Iran)

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## ABSTRACT

*Water quality assessment provides a scientific basis for water resources development and management .Climate change is changing our assumptions about water resources. We used to of samples 372 in Bazoft river that they collected by CBRW in 1975-2012. In this article, we did analysis relation discharge and %NA, SAR, TDS and EC in Bazoft River. We used to use of ANN model for the analysis effected discharge on amount concentration in this basin. The results shown that correlation rate are between discharge to EC (0.62) and TDS (0.75).So they are between discharge to %NA (0.59) and SAR (0.45).According it minimum epoch is for TDS (21) and maximum epoch is for %NA (420). The analysis effect discharge on %NA and SAR at months( Mar, April ,May, June and July) that discharge decreasing has amount concentration is decreasing. Furthermore the analysis effect discharge on %NA and SAR in annually shown that if discharge is creasing then amount value %NA and SAR is creasing too. But about TDS and EC this relation is reversed. These changes are forming soil and geology formation erosion and salt dome.*

**Keywords:** Climate change; Water quality; Concentration; ANN; Bazoft river

## INTRODUCTION

Water quality assessment provides a scientific basis for water resources development and management [1-7]. Climate change is changing our assumptions about water resources. As climate change warms the atmosphere, altering the hydrologic cycle, changes to the amount, timing, form, and intensity of precipitation will continue. Other probable changes include the flow of water in watersheds, as well as the quality of aquatic and marine environments. These impacts are likely to affect the programs designed to protect water quality, public health, and safety.

The quality of a water body is usually characterized biological, chemical, and physical characteristics of water in connection with intended use(s) and a set of standards [4], [8-11]. Therefore, water quality evaluation can be distinct as the assessment of the biological, chemical, and physical properties of water in reference to natural quality, human health effects, and intended uses [8]. Water quality could suffer in areas experiencing increases in rainfall. Increases in heavy precipitation events could cause problems for the water infrastructure, as sewer systems and water treatment plants are overwhelmed by the increased volumes of water [12-15]. Heavy downpours can increase the amount of runoff into rivers and lakes, washing sediment, nutrients, pollutants, trash, animal waste, and other materials into water supplies, making them unusable, unsafe, or in need of water treatment [5].

Harmful effect of climate change may make worse in the future because of growing industry and decreasing attention to the environment. It can also affect on different systems such as water sources, water quality and healthy. Changing in rainfall and temperature patterns will affect hydrological processes, existing water sources and available water for agriculture, drinking, industry, animal life in the river, lakes and hydroelectricity. Effect of climate changing on water sources is assessing using rainfall-runoff models by simulating hydrological processes. Studying future climate change and its likely events will help planners and water sources administrators to cope with future challenge. Predicting future runoff value is one of the most important factors about dam construction, water transferring, and water quality.

Changes in air temperature and rainfall could affect river flows and, hence, the mobility and dilution of contaminants. Increased water temperatures will affect chemical reaction kinetics and, combined with

deteriorations in quality, freshwater ecological status. With increased flows, there will be changes in stream power and, hence, sediment loads with the potential to alter the morphology of rivers and the transfer of sediments to lakes, thereby impacting freshwater habitats in both lake and stream systems. So they showed storms that terminate drought periods will flush nutrients from urban and rural areas or generate acid pulses in acidified upland catchments. Policy responses to climate change, such as the growth of bio-fuels or emission controls, will further impact freshwater quality [16].
The methods three chemo metric data mining techniques (factor analysis (FA), cluster analysis (CA), and discriminates analysis (DA) to identify the latent structure of a water quality (WQ) dataset pertaining to Kinta River (Malaysia) and to classify eight WQ monitoring stations along the river into groups of similar WQ characteristics. These chemo metric techniques highlight the potential for reasonably reducing the number of WQVs and monitoring stations for long-term monitoring purposes [15].
Artificial Neural Networks, and temperature and rainfall input admitted that rainfall – runoff phenomenon can be simulated well.Another searched on water amount of Superior Lake [14]. They restated that change in climate elements has led to50$_{cm}$ decrease in water height in the lake. So for the modeling rainfall-runoff in the two watersheds from China used of artificial neural network coupled with singular spectrum analysis. Results show that MANN does not exhibit significant advantages over ANN [17-19]. To simulate rainfall-runoff in study area, artificial neutral network model with feed forward network and back -propagation applied, which used in 90% of hydrological subjects [2].

## EXPERIMENTAL SECTION

### Study area and data

The Bazoft basin with a 2650-km$^2$ area is a sub basin of Karoon River located in south west of Iran. The origin of Karoon River is in the Zagros Mountain range [18] (Figure 1).Therefore occurrence of any change in effective factors on hydrological factor will follow by important consequences.

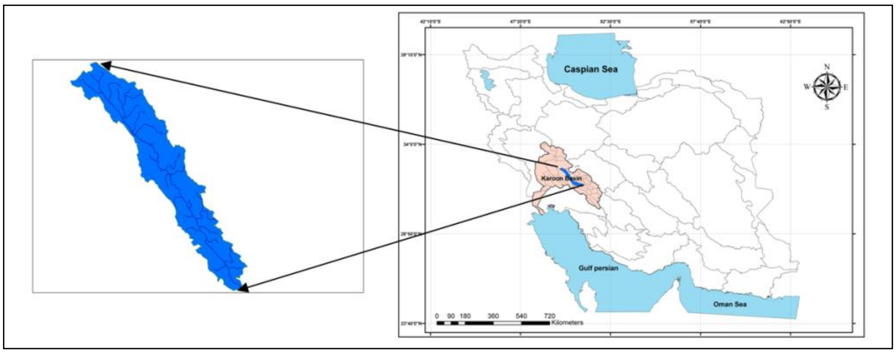


**Figure 1: Locations Bazoft basin in Iran**

The samples are 372.They collected by Chaharmahal and Bakhtiari Regional Water (CBRW) (Table.1) from October 1975 to September 2012.The samples collected do analysis by CBRW. This data are monthly in the time series 1975 to 2012.Monthly measurements of the discharge and water quality variables obtained, and monitored the Marqak station of the Bazoft River by CHRW (Table 1). The following variables measured by CBRW: above (Q) as m$^3$/s, Electrical Conductivity (EC) as µs/cm, Total Dissolved Solid (TDS), Sodium Absorption Ratio (SAR) and %NA temporary hardness and total hardness as meq/l at the above stations (Table1). The monitoring data of these variables are available for the analysis as presented in this paper on monthly and yearly basis for the period of 1981-2013.

**Table 1: The Characteristics of the main stations in Bazoft basin**

| Station | Altitude (m) | Long º | Location Latº | Duration |
|---|---|---|---|---|
| Izeh | 767 | 31° 83ó | 49° 86ó | 2014-1994 |
| Koohrang | 2285 | 32° 43ó | 50° 11ó | 2014-1984 |
| Lordegan | 1580 | 31° 51ó | 50° 81ó | 2014-1994 |
| Marghak(WQ) | 913 | 31° 66ó | 50° 43ó | 2012-1970 |

### Methodology

Monthly average and yearly of the data time series have analyzed by Artificial Neural Network (ANN) methods. In the last two decades, Artificial Neural Network (ANN) has seen an explosion of interest because it is an of use method for prediction, clustering and classification. This approach is becoming an effective and popular another for predictable methods [20],[7],[9]. ANN constitutes intelligent bionic models and the nonlinear, large-scale, adaptive dynamics systems that consist of many interconnected neurons. ANN models have been widely applied to the water quality problems[6]. The fundamental processing element of an ANN is an artificial neuron. Just like the natural neuron in human brain, it can receive inputs, process them and produce the relevant output. A simple mathematical model can be used in explaining a neuron quantitatively (Figure 3). The stimulus functions used here are linear, rad bas and hyperbolic tangent (Equations 1-3).

$$f(x) = \begin{cases} 0 \ if \ x < 0 \\ 1 \ if \ x \ \geq 1 \end{cases} \tag{1}$$

$$radbas(n) = e^{-n^2} \tag{2}$$

$$\varphi(U) = tanh\left(\frac{U}{2}\right) = \frac{1 - exp\ (-U)}{1 + exp\ (U)} \tag{3}$$

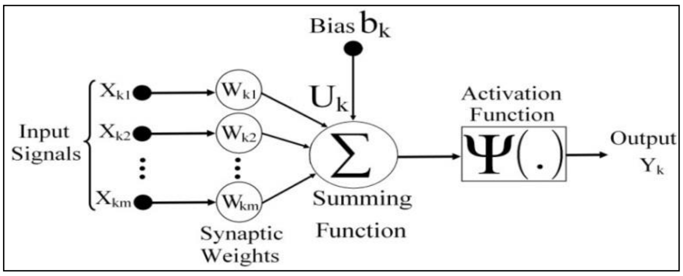


**Figure 2: Modeling a simple neuron [12]**

The networks used in this study are the type back propagation and Radial Basis ones. Back propagation network is a multilayer network with non-linear stimulus function and Wide row-Hoff learning rule. It also uses for the approximate functions and to find a relationship between input, output, and classifying them based on determined ways by the designer (Figure 3).

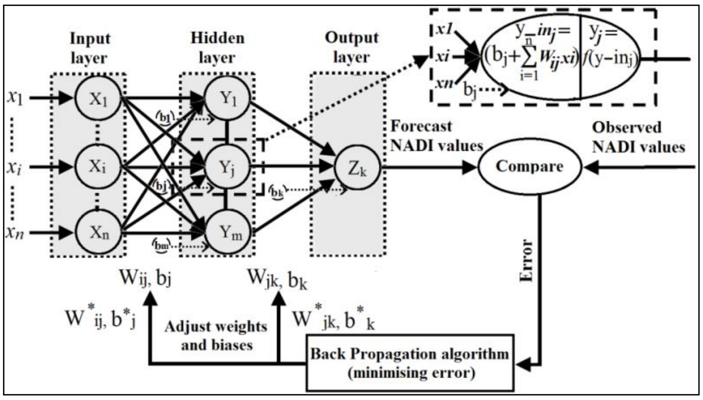


**Figure 3: Multilayer Feed forward network with error back propagation training algorithm [3]**

Training neural networks is done based on the minimum error (MSE) and maximum correlation value [1].To train network, Levenberg-Marquardt algorithm has been used which follows error back propagation rule. This algorithm tries to reduce calculations using lack of Hessian matrix calculation. Matrix Hessian computed as follows:

$$Net_{pi} = \sum W_{ij}\, a_j + b_i \tag{4}$$

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} \tag{5}$$

$$E = \sum_i (obs_i - pre_i)^2 \tag{6}$$

$$Y = \beta + \alpha x_1 + \alpha x_2 + \ldots + \alpha xn \tag{7}$$

Which: ($\alpha$) is a number that controls training process, F is a stimulus function that is non-linear in hidden layers, $\Delta W$ is added to Wij in that $\eta$ is the rate of training and function, multivariate regression method
In addition, besides the results of neural network model, multivariate regression method used in this study to predict rainfall and discharge in Marqak order to determine the performance of these networks by comparing its results with neural network. Multivariate regression model can be calculated as follows:

$$MAE = \frac{\sum_{k=1}^{k} |x_k - y_k|}{k} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{k}(x_k - y_k)^2}{k}} \quad (9)$$

$$X_i^{'} = 0.8*[\frac{X_i - X_{\min}}{X_{\max} - X_{\min}}] + 0.1 \quad (10)$$

In the above equation, Xk is the observational amounts, Yk is the predicted amounts and K is the number of data.

**Simulating rainfall- runoff**

This model has a unilateral structure from input layer toward outer layer. Outer, hidden, and inner layers form it. The number of neutrons in hidden layer calculated by trial and error based on the least error and the highest coefficient. In this study, input of different models of Tmin and Tmax temperature and rainfall with monthly time delay used to simulate runoff. Sigmoid function and Levenberg-Marquardt function are known as the fastest teaching method for Neutral Network. Then statistic models of coefficient, Normal Root Mean Square and Mean Absolute, assessed the model performances in simulating and observing data. Raw data decreases the speed and net accuracy, so input data should be normal and in the interval [0, 0.9] (Equation10) [19].

## RESULTS AND DISCUSSION

To calibrate and ensure performance of ANN, first its codified scenarios for base statistical course based on ANN and during this period the model was performed .Model output values were included rainfall and Standard Deviation. Then they compared with observed data. Output values indicated that there is no significant difference between modeled and observed values for discharge. The results of error- poll tests show appropriate accuracy of model in estimating temperature data (table2). Daily discharge data do not have needed accuracy because of discreteness and randomly selecting of data that the value is zero (days without rainfall) between two rainfall occurrences. So to compute accurate discharge amount a more extensive time interval(monthly)was used because of discharge events approximately during all months(table 2). Monthly discharge analysis shows higher accuracy of model rather than daily time interval. Kohrang, Izeh, Lordegan (mountainous and semi mountainous stations) showed a decreasing rainfall in January, February and December. Rainfall in February decreases in most stations. Future rainfall will decrease 10-36% over Bazoft Basin.

**Sensitivity analysis and rainfall estimating**

To validate and calibration the Artificial Neural Networks model the data of base course divided into two parts: teaching and testing 70% of data studied for teaching part and 30% for testing. The output of this model is monthly discharge amount of hydrometric stations. Neuron structure, middle layers and time delays in input factors studied to determine the best model for runoff calculating. The results of different structures mentioned in table2. The best structure applied daily discharge with 1 and 2 – month time delay, and structure of neurons are 18, 10, and 18with 3 middle layers (Figure 4). According to coefficient statistical values and low error, the model could estimate the runoff well.

**Table 2: Output Artificial Neural Networks in the Marqak station**

| Stations | Layers Structure | Epoch | Test | | | Train | | |
|---|---|---|---|---|---|---|---|---|
| | | | MAE | RMSE | R | MAE | RMSE | R |
| Marghak | 8-8-8-1 | 49 | 0.0229 | 0. 1803 | 0.58 | 0.0024 | 0.0282 | 0.97 |

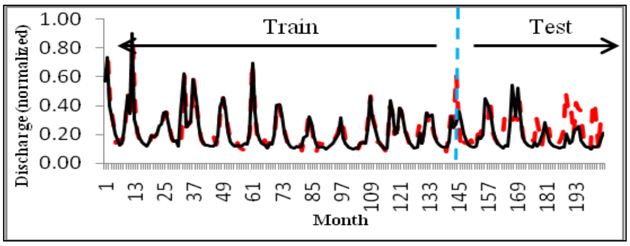


**Figure 4: Time series of hydrometric marqak station inflow simulated by ANN in observation period**

The results of modeling for inputs in two examination and testing series shown in figure 5. Therefore, they indicated that according to the final structures of neurons, the model is performing well in result estimating and simulating flow amounts in base course these models used to stimulate the future runoff. Then the runoff calculated under data of ANN scenario during 12 months. Computing runoff of hydrometric station determined that runoff flow decreases during months from March to June and increases during other months (figure 5). Marqak experience increased runoff in the fall and decreased one in the summer.

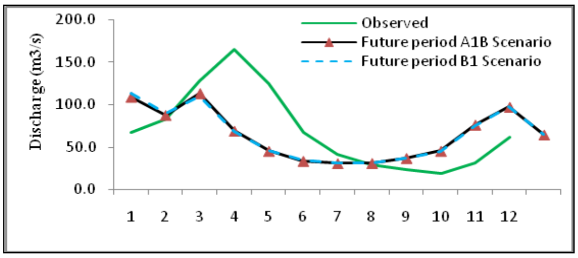


**Figure 5: Long-term Inflow to marqak station hydrometric in observed & future period**

Yearly runoff decreases in Marqak station. The most increase in the future runoff belongs to the fall. The yearly increase in runoff saw in Marqak to the amount of 10, 7, and 15% respectively. Future runoff decreases from 35 to 60 % during April, May, and June. Geology formations have the main role in decreasing water quality in this basin. The annual precipitation mean in this basin is 800 mm with an annual water volume of 2.7 billion $m^3$. The formation of this basin is sedimentary. Lithology of the rocks is limestone, marl, sandstone, dolomite and gypsum. In addition, formation of Hormuz complex (Nazi Dome salt) contain salt red, marl, sandstone and red shale with an igneous composition. In terms of tectonic, Bazoft affected by Zard-koh and Bazoft faults. This fault is parallel to main Zagros fault direction. Geologically, Hormmoz Formation is the oldest known formation in this area with an age from pre Cambrian to middle Cambrian (Fig.6). The type of Hormmoz formation consists of salt, prêt marls with interlayer lime, sandstone and marl. Due to its salt formation feature in the direction of Bazoft Fault, the Hormmoz formation has cut the younger formations and reached the surface, and its facials are Hormmoz formation with northeast-southwest direction. The ANN results showed that ANN model was suitable for water quality in Marqak station.

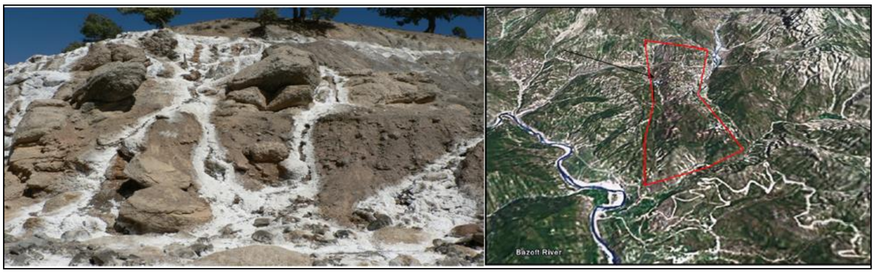

**Figure 7: The Situation Nazi salt dome in bazoft**

The results show that correlation rate are between discharge to EC (0.62) and TDS (0.75).So they are between discharge to %NA (0.59) and SAR (0.45). Table.3 show results ANN modeling. According it minimum epoch is for TDS(21) and maximum epoch is for %NA(420).In additional results compare test and training shows that output ANN model for water quality is suitable in Marqak station(Figure 7).

**Table 3: Output Artificial Neural Networks the water quality elements in marghak station**

| Element | Layers structure | Epoch | Test | | | Train | | |
|---|---|---|---|---|---|---|---|---|
| | | | MAE | RMSE | R | MAE | RMSE | R |
| %NA | 20-20-1 | 420 | 0.0113 | 0.1206 | 0.86 | 0.0038 | 0.0619 | 0.59 |
| SAR | 13-13-1 | 81 | 0.0021 | 0.0335 | 0.71 | 0.0072 | 0.077 | 0.45 |
| EC | 15-15-15-1 | 109 | 0.0054 | 0.0867 | 0.87 | 0.0158 | 0.1681 | 0.62 |
| TDs | 37174 | 28 | 0.0056 | 0.0896 | 0.85 | 0.0091 | 0.964 | 0.75 |

The analysis effect discharge on %NA and SAR at months( Mar, April ,May, June and July) that discharge decreasing has amount concentration is decreasing too(Figure 8). Also as the discharge is increasing amount concentration is increasing too. So these changes are forming soil and geology formation erosion and salt dome. Furthermore the analysis effect discharge on %NA and SAR in annually shown that if discharge is creasing then amount value %NA and SAR is creasing too. But about TDS and EC this relation is reversed (Figure 9).

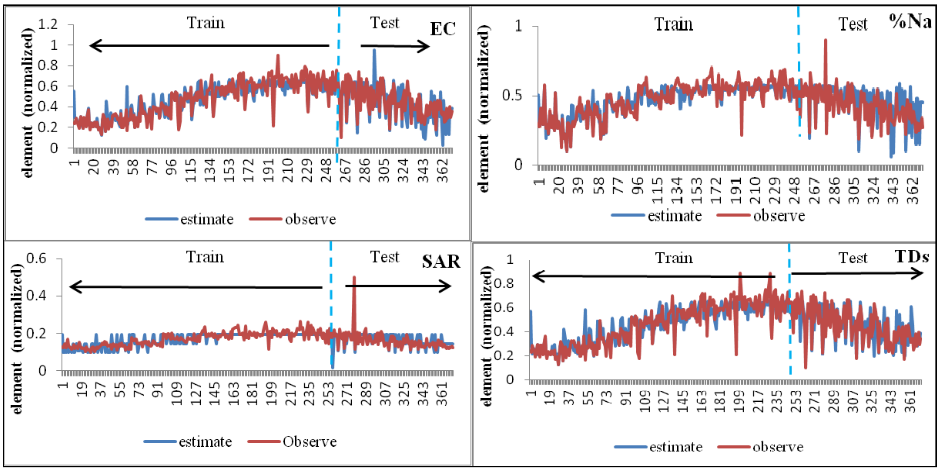


**Figure 7: Time series of hydrometric marqak Stations the water quality elements simulated By ANN in observation period**

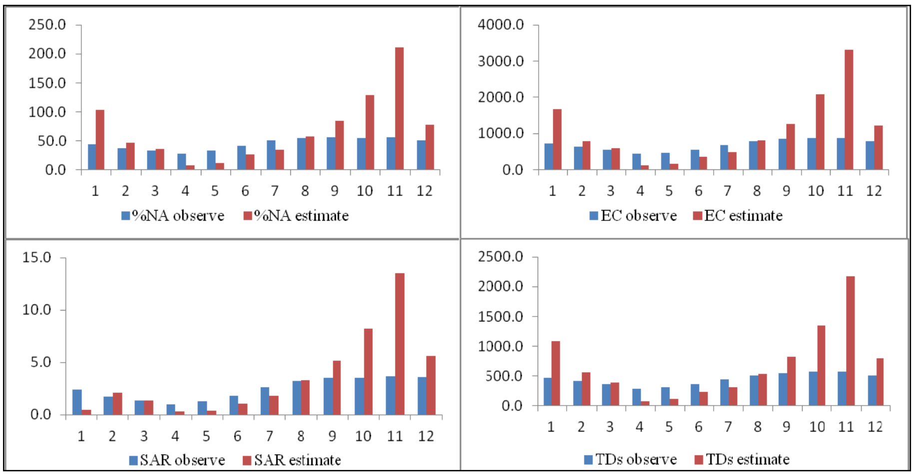


**Figure 8: The water quality of monthly amount in Marqak station**

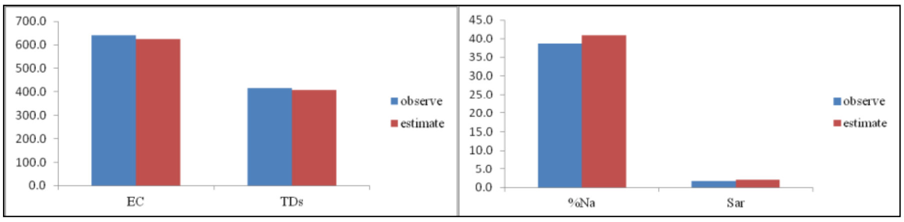


**Figure 9: The water quality of elements amount annual in Marqak station**

## CONCLUSION

World decrease in future water source is a serious challenge especially in areas with arid and semiarid climate such as Iran in which water sources are generally dependent on micro geographical regions. Water quality assessment provides a scientific basis for water resources development and management .Climate change is changing our assumptions about water resources. We used to of samples 372 in Bazoft river that they collected by CBRW in 1975-2012. In this article, we did analysis relation discharge and %NA, SAR, TDS and EC in Bazoft River. We used to use of ANN model for the analysis effected discharge on amount concentration in this basin. The results shown that correlation rate are between discharge to EC (0.62) and TDS (0.75).So they are between discharge to %NA (0.59) and SAR (0.45).According it minimum epoch is for TDS (21) and maximum epoch is for %NA (420). The analysis effect discharge on %NA and SAR at months( Mar, April ,May, June and July) that discharge decreasing has amount concentration is decreasing. Furthermore the analysis effect discharge on %NA and SAR in annually shown that if discharge is creasing then amount value %NA and SAR is creasing too. But about TDS and EC this relation is reversed. These changes are forming soil and geology formation erosion and salt dome.

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