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# Comparison of Using Different Systems of Artificial Intelligence in Subsurface Water Level Prediction (Case Study: Paddy Fields of Plain Areas between Tajan and Nekaroud Rivers, Mazandaran, Iran)

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**ABSTRACT:** Novelty of the implementation drainage system in paddy fields and studies in this case led to the observation wells network with sufficient data does not exist in the northern region of the Iran and consequently does not provide access to subsurface water level of long-term data. Due to the complex and nonlinear behavior of subsurface water systems and to consider many factors affecting it, it seems to be difficult to predict the groundwater level. In this research, Artificial Neural Network (ANN) and Neuro- Fuzzy inference system (ANFIS) is used to predict the subsurface water level in paddy fields of Plain Areas between Tajan and Nekaroud Rivers. The results indicated by removal the wells that water depth is zero in them can be achieved reasonably accurate in predicting subsurface water depth in the study area and ANN with tangent sigmoid transfer function and with five neurons in the hidden layer and ANFIS with subtractive clustering and range of influence equal to 0.7 have almost the same accuracy in predicting the depth of subsurface water because the correlation coefficient of these two models are Respectively 0.8416 and 0.8593 and RMSE of them is 0.2667 and 0.2491.

***Keywords***: Prediction of subsurface water level, Artificial intelligence, Artificial Neural Networks, Adaptive Neuro-Fuzzy inference system.

## INTRODUCTION

Control of drainage conditions in paddy fields is essential. Because on the one hand, the lack of proper drainage system in the soil will cause toxicity and toxicity caused by poorly drained soils can lead to physiological disorders such as Akagare. Therefore, the timely land drainage can be driven oxygen into the soil and toxic gases resulting from the reduction of iron and manganese away from the root zone (Okhovvat and Vakili, 1997). On the other hand, Iran is greatly needed to increase production, especially in the forage crops and oilseeds, attention to the necessity to increase the income of farmers of northern lands is mostly planted not more than once a year show importance of developing second crop cultivation in paddy fields as a basic necessity (Yazdani et al., 2007).

One of the main indicators of the design, implementation and operation of surface and subsurface drainage systems in paddy fields is water flow treatment between the ground and subsurface hard pan. Hard pan is a layer dedicated to paddy fields and is usually formed at a depth of 20 to 30 cm. It causes high resistance in the soil and facilitates the cultivation. So, the absence of this layer lead to sinking the tillage implements (Shi-Kai and Chan, 2002).

The results of the studies in Mazandaran Province Land Drainage Studies show that considering importance of hardpan maintenance in the paddy fields, the major problem in land drainage is removal of surface and subsurface run off to create favorable conditions for soil aeration and drainage before secondary cultivation.

It is necessary and inevitable to determine the depth of subsurface water flow through the watertable contour map, hydraulic conductivity, lower layers of soil transmission coefficient and subsurface flow volume estimation. But novelty of the implementation drainage system in paddy fields and studies in this case led to the observation wells network with sufficient data does not exist in the northern region of Iran and consequently does not provide access to subsurface water level of long-term data. So, these reasons would justify the need for research on different methods of subsurface water level prediction and evaluate their accuracy.

Considering the behavior of subsurface water systems is complex, non-linear and affected by many parameters, it seems difficult to predict the water level. However, little research has been done on the subsurface water flow models specifically and most models offered by different researchers have been proposed to predict the groundwater level.

In comparison, the physical models are essential tools for the study of such variables, but they have practical limitations. Another problem with this model to simulate is the need for accurate and diverse inputs, such as soil characteristics. Also, each model requires a long time and in most optimization processes, it is necessary to simulate the water table level is continuous with respect to time. Therefore, these factors makes the use of these models to evaluate different approaches would be time-consuming, difficult, and sometimes impossible (Nourani et al., 2007).

A common method for solving nonlinear groundwater is using artificial intelligence systems. Artificial intelligence systems that used in this study are, Artificial Neural Network(ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) (Kia, 2012).

In Chung's doctoral (PhD) thesis, (2008), two ANN-based prediction models was used to estimate the fluctuations in the water table in the area of Maryland. The root mean square errors of the water table forecasts for 12 months were between 0.043m and 0.047m for these models. The results of sensitivity test showed that the models were more sensitive to the uncertainty in water table depth than to that in brightness temperature or in soil moisture content.

In Joorabchi and et al, (2009) study, Artificial Neural Networks are adapted to simulate groundwater table fluctuations. The trainig data was based on field measurements from five different locations down of Australia's east coast. The results from the Developed model have shown that ANN model is very successful in terms of the prediction of a target that is dependent on a number of variables.

In other research, Sreekanth et al (2009) standard feed-forward neural network trained with Marquardt Levenberg–algorithm was examined for forecasting groundwater level at Maheshwaram watershed, Hyderabad, India. The model provided the best fit and the predicted trend followed the observed data closely (RMSE = 4.50 and $R^2$ = 0.93).

Kavitha and Naidu, (2011) compared the efficiency of two computational intelligence techniques in groundwater level prediction of a Thurinjapuram watershed in Tamilnadu, India. The techniques under comparison were Artificial Neural Networks (ANNs) and Fuzzy Logic (FL). A three-layer feed-forward ANN was developed using the sigmoid function and the back propagation algorithm. The FL model was developed employing the Gaussian fuzzy membership functions for the input and output variables. In this study it was observed that ANNs perform significantly better than FLs.

In the study of Dehghani et al, (2009) different approaches such as geostatistics (Kriging), neural networks (MLP and RBF) and adaptive neuro-fuzzy inference system (ANFIS) is evaluated in order to identify the best approach for interpolation in groundwater level estimation. Qazvin aquifer was chosen as the case study for this study. The results showed that accurate predictions can be achieved with an adaptive neuro- fuzzy with $R^2$=0.98. Due to smaller amount of MSE, the MLP neural networks with $R^2$=0.93 can give more accurate results than RBF ($R^2$=0.9) and kriging methods ($R^2$=0.95).

Mohtasham and et al, (2010) in their research divided Birjand plain, Iran to sixteen polygons (according to sixteen piezometric wells) by using Thiessen's polygon approach. Then in each polygon the amount of recharge (due to precipitation) and discharge (due to pumping wells) were calculated and selected as input parameters in addition to groundwater level of previous month. The groundwater level in present time was selected as output parameter in artificial neural network. The results show that artificial neural networks can simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 12 months ahead ($R^2$=0.99, MSE=0.032).

In this research, considering the importance of subsurface water level in the drainage plan and the limitations of existing data, the accuracy of two artificial intelligence systems, ANN and ANFIS, is evaluated in predicting subsurface water depth in paddy fields of Plain Areas between Tajan and Nekaroud Rivers, Mazandaram, Iran.

## MATERIALS AND METHODS

### *Study area*

Study area (Area ≈350 $Km^2$) is located in the southeast of the Mazandaran Lake and north of the Sari-Neka main road. It is called Tajan plain. Geographically, the plains are located between eastern longitudes 52 º 5' and 53 º 15', and northern latitude 36 º 25' and 36 º 50' (Figure 1). Sari, provincial capital, and Miandoroud are the most important cities of this area, which are located in the south of the study area (Abgstran-e-Sabzdasht Consulting Engineers, 2012).

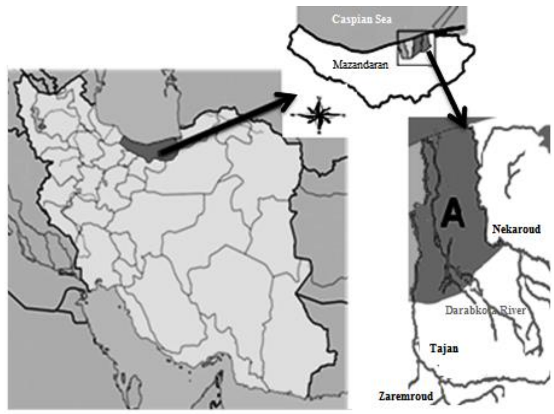


**Figure1.** Plain Areas between Tajan and Nekarood Rivers, Mazandaran, Iran

### *Artificial Neural Networks(ANN)*

Artificial neural network is a mathematical model, which has the capability of modeling and nonlinear relationships setting for Interpolation. A neural network model is formed of three layers: input, hidden and output. There are one or more neurons in each layer and each neuron is connected to all neurons in the next layer. The number of neurons in the input layer is equal to the number of independent variables of the system. Each of the input layer neurons are multiplied by a weighting factor. The weighted factor value determines the effect of each variable on the performance of input layer (Menhaj, 2002).

### *Network Training*

The concept of training in artificial neural networks is that the weighting factor is calculated. Back propagation algorithm is composed of two main paths. In the first path, called the "Forward path", the input vector applied to the network and its influence spread through intermediate layers to the output layer. In this way the network parameters are assumed to be constant and unchanged. The second path is called "Backward path". In this path, unlike the previous, the network parameters are changed and adjustable. Error vector is equal to the difference between the desired response and the actual response of the network. Error value is distributed in the whole of network after calculating on the return path from the output layer and through the network layers.

### *Adaptive Neuro-Fuzzy Inference System (ANFIS)*

ANFIS has a good ability in training and classification and also has the advantage that it allows to extract fuzzy rules from numerical data or expert's knowledge.

ANFIS suitable structure is selected according to the input data, type of inputs and outputs membership functions, and rules and the number of membership functions. In this model, there are two methods of subtractive clustering and grid partition to partition the first part of fuzzy rules (Chang and Chang, 2005).

In this method, for a, a "set of sample rules" can be expressed by two rules "if - then" phase as follows:

First rule: if x equal to $A_1$and y equal to $B_1$, then $z_1 = p_1x + q_1y + r_1$

Second rule: if x equal to $A_1$ and y equal to $B_2$, then $z_2 = p_2x + q_2y + r_2$

Where $p_i$, $q_i$ and $r_i$ (i = 1, 2) are linear parameters of first order Takagi-Sugeno fuzzy model.

This network is trained by supervised learning. So our goal is to train adaptive networks which are able to estimate the unknown functions from train data and to find the exact value of to above parameters (Jang et al., 1997).

Finally, the distinguishing feature of ANFIS is providing hybrid learning algorithm and using the least squares method and the gradient slope to modify the parameters.

To evaluate the efficiency of the model was used variables correlation coefficient ($R^2$), Root Mean Square Error (RMSE), and Mean of Absolute Error (MAE) according to the following equations:

$$R^2 = \sqrt{1 - \frac{\sum (X-Y)}{\sum X^2 - \frac{\sum Y^2}{n}}} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum (X-Y)^2}{n}} \quad (2)$$

$$MAE = \frac{\sum_{i=1}^{n} |X-Y|}{n} \quad (3)$$

Where X: the observed values, Y: predicted values and n: number of data.

Since the raw data may cause to reduce accuracy and speed of network and in order to equalize the value of the data using the following equation data normalized between 0 and 1.

$$X_{norm} = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})} \quad (4)$$

***Research methodology***

In order to study the status of groundwater level in the lands of study, it is used data from 90 observation wells were excavated to a distance of about 2 km apart. The position of the observation wells is shown in Figure 2.

Due to the similarity of the climate of the land area is used daily weather data from Dasht-e-Naz (in Miandoroud City) synoptic stations within the study area.

The number of neurons in input layer equals the number of independent parameter in network. In this study, the input parameters include the volume of water entering the Polygon $V_{in}$ (t) ($m^3$) that is equal to the amount of precipitation in the Polygon area of each well, the exiting volume of water in each polygon $V_{out}$ (t) ($m^3$) that is evapotranspiration was calculated using evaporation pan in the Polygon area of each well, average temperature T (t) In each period and the groundwater level in the previous period, $W_t$ (t-1). The number of neurons in the output layer was chosen equal to network output (groundwater level at the end of each period, $W_t$ (t)). Also, the number of neurons in the middle layer was determined by trial and error.

Thiessen polygons are used to put the physic of problem in the network input variables and also to be considered the spatial variability of parameters in land surface. It is clear that the consideration Thiessen polygon for each variables, can significantly affect the results of the network (Coppola et al., 2003).

Of all available data, 75% is used for training and 25% for testing. By Matlab R2010a Software, to achieve the best configuration of the ANN is used error back propagation algorithm and for ANFIS is used Takagi-Sugeno model with subtractive clustering .ArcGis10 software are used to draw Thiessen Polygon and calculate the area of each Polygon.

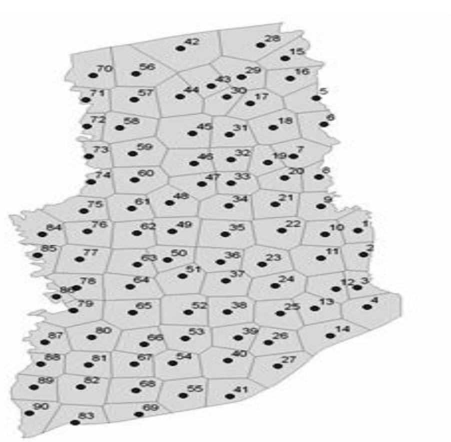

**Figure 2 - Location of boreholes in the study area and Thiessen Plygon of each boreholes**

## RESULTS AND DISCUSSION

To achieve the best model to predict groundwater level, the study was done in four states. In the first mode after removing outliers, it was used all wells data which led to a total of 405 data series. In this mode, artificial neural network with error back propagation algorithm, and tangent sigmoid transfer function in the hidden layer and 6 neurons in the middle layer provides more accurate results. Neuro-Fuzzy Inference System is also indicated Sugeno model of the Grid Partition method does not produce acceptable results, especially in the testing, so the Subtractive Clustering method was used. The results also show that by changing the range of influence index to 0.7, the best test results obtained. In fact, a decrease in this parameter compared to default value of 0.5, increased accuracy during the training but decreases its efficiency in the testing and the increased this value will occur contrary to the previous state.

In the second mode, due to the low accuracy of the models in predicting water levels, with the assumption that most of the wells that water level elevation is recorded equal to zero at them were located near the major rivers and removing them will not make a dent on the nature of the problem, the recorded data of these wells was eliminated from the model inputs. Table 1 also shows the results of evaluating the best possible arrangement, based on 230 data sets, after several iterations in this state. In this mode, the ANN tangent sigmoid transfer function in the hidden layer and 5 neurons in the middle layer, and the ANFIS by Subtractive Clustering with range of influence equal to 0.7 has provided the best results.

Table1. Summary of the best results to predict the groundwater level

| row | Model | State | Train $R^2$ | RMSE | Test $R^2$ | RMSE | MAE |
|---|---|---|---|---|---|---|---|
| 1 | ANN | All wells | 0.75244 | 0.5240 | 0.4495 | 0.6076 | 0.3678 |
| 2 | | Elimination of Zero recoded wells | 0.8028 | 0.2403 | 0.8614 | 0.2667 | 0.2123 |
| 3 | ANFIS | All wells | 0.5411 | 0.5116 | 0.4482 | 0.5962 | 0.3629 |
| 4 | | Elimination of Zero recoded wells | 0.7684 | 0.3686 | 0.8593 | 0.2491 | 0.1928 |

Table 1 shows that although both of artificial intelligence systems has low accuracy in fist mode (using data from all observation wells), but in the second mode by removing the zero wells increased accuracy, so that $R^2$ coefficient are grown from 0.45 to 0.85. However, the accuracy of prediction groundwater level in the study area is almost the same in both models.

Finally, ANN leads to a more accurate model of the training function TRAINLM and the stimulus function TANSIG, with 5 neurons in the middle layer rather than the LOGSIG functions and PURLN and its best $R^2$= 0.8416 and RMSE = 0.2667 (Fig 3.). These results are corresponded with studies Mohtasham et al., (2010) and Sreekanth et al (2009). Also ANFIS by Subtractive Clustering with range of influence equal to 0.7 has provided the best results and its best $R^2$=0.8593 and RMSE=0.2491 (Fig 4.) Therefore, the results obtained with results of Kavitha and Naidu (2011) is quite corresponded.

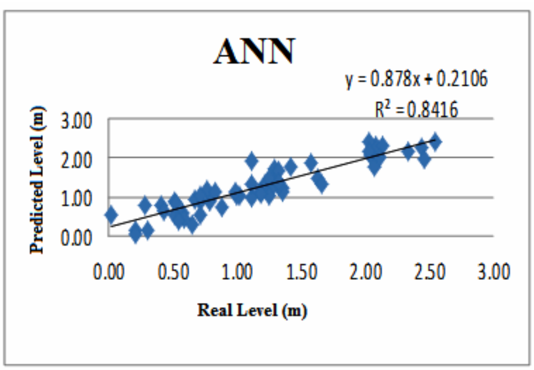


**Figure 3 - Groundwater Level Prediction with ANN Pattern 2 of table 1**

This accuracy compared to other studies, such as Dehghani and et al, (2009) seems to be less; it could be the main reasons as follows:

Due to lack of necessity, record water level and data collection in the subsurface flow, unlike underground flows has been very limited. So the difference in the number of observation wells could be one reason for the decrease in accuracy

One of the major approaches in this study is evaluation the ability of artificial intelligence models to predict subsurface water level in a vast plain area (not just within a single well) using the data of all existing wells. Thus, as a remarkable achievement, It was shown apart from the fact that these models are able to predict the subsurface water level of an observation wells based its long term data, If the recording level is the most precise and systematic, Is also able to predict water level less accurate but acceptable in a region based on all existing wells. Therefore, in many phases of the study of consulting engineers, such as subsurface drainage studies, that observation wells excavation and recording their data are required for subsurface water level studies and while the long term water level elevation data do not exist in the early stages of studies, this modeling approach can be of great help to analyze subsurface water.

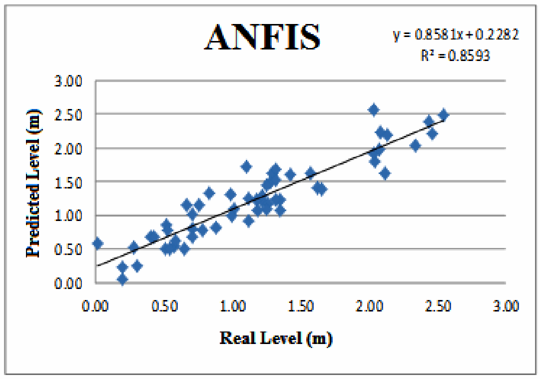


**Figure 4 - Groundwater Level Prediction with ANFIS Pattern 4 of table 1**

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