Groundwater level simulation using artificial neural network: a case study from Aghili plain, urban area of Gotvand, south-west Iran

Manouchehr Chitsazan, Gholamreza Rahmani*, Ahmad Neyamadpour
Faculty of Earth Sciences, Shahid Chamran University, Ahvaz, Iran
**Corresponding author, e-mail: Gholamreza90@yahoo.com*
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Abstract

In this paper, the Artificial Neural Network (ANN) approach is applied for forecasting groundwater level fluctuation in Aghili plain, southwest Iran. An optimal design is completed for the two hidden layers with four different algorithms: gradient descent with momentum (GDM), levenberg marquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG). Rain, evaporation, relative humidity, temperature (maximum and minimum), discharge of irrigation canal, and groundwater recharge from the plain boundary were used in input layer while future groundwater level was used as output layer. Before training, the available data were divided into three groups, according to hydrogeological characteristics of different parts of the plain surrounding, each piezometer. Therefore, FFN-LM algorithm has shown best result in the present study for all three hydrogeological groups. At last, to evaluate applied division, a unit network with all data and using LM algorithm was trained. Validation of the network shows that dividing the piezometers into different groups of data and designing distinct networks gives more focus on simulating groundwater level in the plain. The degree of accuracy of the ANN model in prediction is acceptable. Thus, it can be determined that ANN provides a feasible method in predicting groundwater level in Aghili plain.

Keywords: *Artificial neural network, Forward neural network, Simulation, Groundwater level*

Introduction

Groundwater always has been as one important resource to supply drinking and agriculture water especially in arid and semi-arid region. These resources commonly have a high quality, usually do not need chemical treatment, and commonly are free of pathogenic factors. All these reasons make groundwater an important and reliable resource in supplying consumption needs of different users (Firouzkouhi, 2011). Groundwater Reservoir (aquifer) is a complicated system that is exposed to either Natural or artificial factors that creates tensions on the overall system of aquifer in different chronological levels that their result is the fluctuations of groundwater level. Thus, to exploit and manage groundwater, models are needed to predict groundwater level fluctuations. Nowadays, because of developing and progressing of computer, using mathematical models for groundwater level forecasting has a significant development. A big problem that user and suppliers of these models are faced now is the needs of these models to exact and various input data. Artificial neural networks (ANN) which are driven from biological neural networks can help solving such problems. These networks that are apart of intelligent systems having developed with various and spread structures. ANN especially is useful if nonlinearity exists in a problem, domain (Taslloti, 2004). Many works related to hydrology have used artificial neural networks (ANN) as a research tool. Aziz and Wong (1992) used artificial neural networks for the first time to determine aquifer parameters .They illustrated the use of ANNs for determining aquifer parameter values from normalized drawdown data obtained from pumping tests. Using measured drawdowns as inputs, neural networks were trained to yield transmissivity T, storage coefficient S, and the ratio r/B, where r represents the distance to the observation well and B is the aquifer thickness. Both confined and leaky-confined aquifers were considered. A three layers network was trained with data generated from the Theis and Hantush-Jacob solutions. After training, the ANNs were tested on two sets of field data. The values of aquifer parameters predicted by the ANN compared well with results using traditional methods (ASCE) Task Committee on the Application of Artificial Neural Networks in Hydrology (ASCE, 2000a, b).

Paulin *et al.*, (2001) calibrates three types of artificial neural network models (PNN, GRBF, RNN and IDNN) by using data of groundwater level and hydrometeorology to simulate the groundwater fluctuation in Gondo aquifer.

Coppola *et al.*, (2003) showed that artificial neural network has a high ability in accurate predicting of groundwater level fluctuations in an unsteady state of an aquifer influenced by pumping and different weather condition. They noted the predicted results of artificial neural network are more accurate than quantitative models. They also showed that ANN models are good in simulating karstic and leaky aquifers where other numerical models are weak in such cases.

Comprehensive reviews of the applications of ANN in hydrology have also been presented by Maier and Dandy (2000).

For the first time, artificial neural networks (MLP) were used for evaluating dynamic water level in karstic aquifer by Lallahem *et al.*, (2005).They have shown the potential of ANN for analyzing hydrology and water resource problems. Their results also confirmed the ability of ANN in simulating groundwater level fluctuations of karstic aquifer compared to numerical models. In this study, monthly average temperature, monthly average evaporation, rain, efficient rain, and fluctuation of water level in thirteen available piezometers in the study area were, input data.

In another study by Taiyuan *et al.*, (2007) the effects of hydrological, weather and humidity conditions on groundwater level weresimulated by neural networks in low part of Shenyang river basin, North West of china. The used ANN model was able to predict groundwater level with the average of error 0.37 or lower with the high accuracy.

Steyl (2009) reviewed the application of artificial neural networks algorithms in geohydrology. Function of artificial neural network model (standard neural network) trained by LM algorithm to predict fluctuation of groundwater level was examined in the basin of Maheshwaram in India's Heidar Abad by Sreckanth *et al.*, (2009). The model efficiency and accuracy were measured based on the root mean square error (RMSE) and regression coefficient (R). They implied that ANN appears to be a promising tool for precise and accurate groundwater level forecasting.

Nadiri (2007) had dealt with evaluating of artificial neural network(FFN-LM) ability in modeling of complex aquifer of Tabriz.

The main purpose of this article also is using artificial neural networks especially feed forward back propagation neural networks to simulate and predict groundwater level. Aghili plain in Khuzestan province, south west of Iran was chosen as the study area as its groundwater resources have being overexploited during the last fifteen years and the groundwater level has been decreasing steadily. Different types of network architectures and training algorithms are investigated and compared in terms of model prediction efficiency and accuracy.

First, the network was designed and efficient parameters in designing and conducting the network were achieved. Then, the model evaluated the performance of four algorithms LM, RP, GDM, and SCG.

The study area and data

The study area is Aghili plain, located in north east of Khuzestan province, Iran. Aghili plain is located between 49´ and 48" and 58´ and 48" longitude and between 6´ and 32" to 16´ and 32" of northern for latitude (fig. 1). The average of annual rainfall in 39 years is 404.81 and for the year of 2009-2010 is 330 mm.

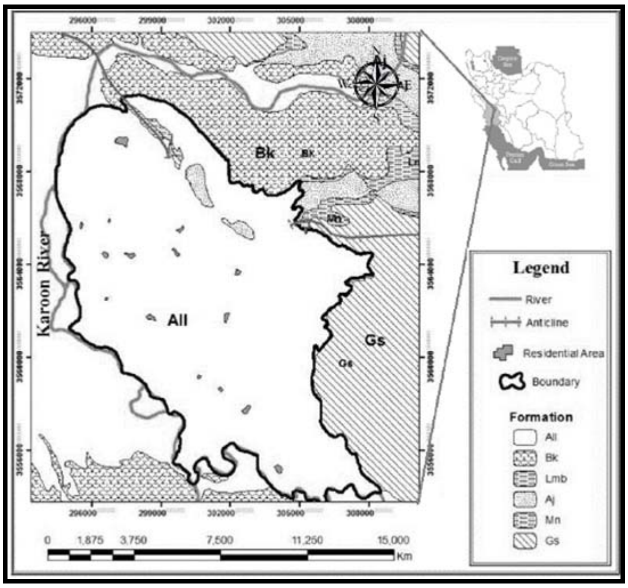

Figure1: Geology map and Geographic location of the study area

Hydrogeology of plain

Aghili is an alluvial plain that was deposited by Karun River and its neighbor formation and plain's area is 142.41km^2 (Nejati Jahromi, 2009). Aghili plain has arid and dry climate. Aquifer of Aghili plain is unconfined and formatted of tow sedimentation cycle.

These cycles are result of erosion in aghajari and bakhtiary formation. There is fourty pumping well in plain.

Data

The available required data to simulate groundwater were rainfall during 39 years, average monthly temperature (monthly minimum and maximum) during 39 years, evaporation during 39 years, relative humidity during 25 years and discharge of irrigation canals during a period of 10 years. These data with one-month time step were introduced to the ANN as input. Water level of plain piezometers was available for eight and half years. The groundwater recharge from eastern boundary of plain also was considered as input data to the model. For this purpose, by applying Darcy law and using aquifer transmissivity and slope, groundwater recharge from boundary was calculated. The width of eastern boundary also was calculated using ArcGIS10.

Base of selecting these data, has been previous studies such as Lallahem *et al.,* (2005) Nadiri (2007), Mirarabi (2009), etc. and according to the data available in the area. Rain is the main factor affecting the groundwater level. Evaporation, relative humidity, temperature selected according effective in climate and so depth of water level in study area (that is 2-28 meter). Discharge of irrigation canal including discharge rate of pumping well and return agriculture water and discharge of boundary also is a charging for aquifer.

To design network, analogues output and input data of the same period with an equivalent time step were used. Therefore, according to available data of water level (main goal in this study) in piezometers, the other data, from October 2002 to January 2011, were selected and time step for all data is monthly.

Methodology

Artificial Neural Network

The general structures of the artificial neural networks were driven from human neural networks. These structures are about able to function like biological neural system but in smaller size and dimensions. By processing the available data they transfer and preserves the hidden rule behind the network structure, because this, they have been called Intelligent. For the first time, a basic artificial neural network model was presented by McCulloch and Pitts (1984). From that time up to now, about 30 models of neural network with different structure were suggested. At the present, using neural networks in water sciences is extending fast because the artificial neural networks can simulate complicated processes with different influencing causes. Today, to predict and understand the temporal and spatial relations between effective parameters in groundwater level, modern techniques are used (Rosmina *et al.,* 2007). Artificial neural network is one of these modeling techniques that are applied for groundwater simulation more than two decades. These networks were driven from human brain and training and learning rules (Menhaj, 2008). In fact, an artificial neural network model is a model of block box that only can be reached from training and learning the hidden and complicated relations that exists among the phenomenon. The nonlinearity that is not understandable by the statistics methods can be handled by ANN. These models need fewer data to perform simulation. Also, they have a high processing ability and can execute the management scenarios very fast and can be a good alternative for mathematical models.

The predicted models that were achieved by artificial neural network are more conductive than linear models and even other nonlinearity models such as phase model. These models have different type that one of the most usable of them especially in water sciences is, feed forward back propagation neural network that has been used in this article.

A simple neuron

The most basic starting point in artificial neural networks is the simple neuron with a single scalar input and no bias (Fig. 2, left side) Hagan *et al.*, 2002. The scalar input p is transmitted through a connection that multiplies its strength by the scalar weight w to form the product wp which is again a scalar value. The weighted input wp is the only argument of the transfer function f, which produces the scalar output a.

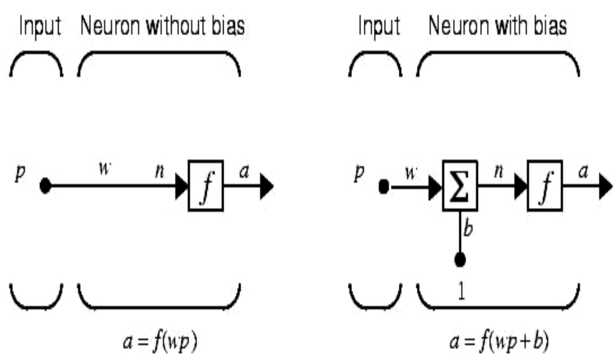

Figure2: A simple neuron with no bias (left side) and a neuron with a bias factor implemented (right side), Hagan *et al.*, 2002

The neuron on the right in Fig. 2 has a scalar bias, b. The bias is simply the addition of a value to the product of wp, it acts as an if it is shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of one. The transfer function net input n, again a scalar, is the sum of the weighted input wp and the bias b. This sum is the argument of the transfer function f. Here f is a transfer function, typically a step function or a sigmoid function, that takes the argument n and produces the output a . It should be noted that w and b are both adjustable scalar parameters of the neuron and can be adjusted so that the network exhibits some desired or interesting behavior (Steyl, 2009).

Feed Forward Back Propagation Neural Network

The term, “feed- forward” describes how the neural network processes and recalls patterns. In a feed forward neural network, neurons are only connected forward. Each layer of the neural network contains connections to the next layer (for example, from the input to the hidden layer), but there are no connections back. Feed forward back propagation neural networks (FFN-BP) are relative new tools in the earth sciences (Uddameri, 2006; Gidson, 2009). These are supervised networks. Process of learning is as follows:

Artificial neurons send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an output layer. There maybe or more intermediate *hidden layers*. The back propagation algorithm uses supervised learning, which means that algorithm with examples of the inputs and outputs are provided to network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN *learns* the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal. In forward networks, processors nodes are located in hidden layers. Every network can have several hidden layers and every hidden layer can have several nodes (fig. 3).

In these networks, data move from input to the output. Not only the present nodes in one layer do not connect to one another but also they connect in one layer to the next. Therefore, an output node in a layer depends on signals achieved from previous layer, determined weight, and type of transform function (Abd¨usselam, 2007).

Application of neural networks in present study

Three data sets are needed for ANNs: for training, validation and testing the network. The usual approach is to prepare a single data set, and differentiate it by a random selection.

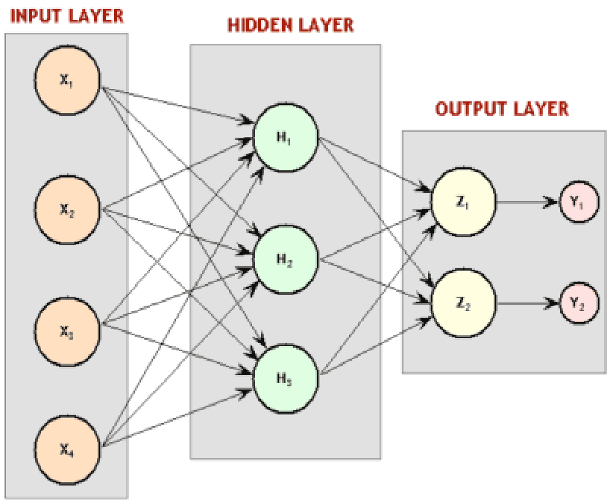

Figure 3: A Two-layer, feed-forward network with four inputs and two outputs (Jones, 2008)

In this study, observed data (rainfall, average monthly temperature (monthly minimum and maximum), discharge of irrigation canals and groundwater recharge from boundary of the study area) were used to train, validate and test an artificial neural-network. The learning algorithm called the back-propagation was applied for the single hidden layer. Scaled conjugate gradient (SCG), Levenberg–Marquardt (LM), gradient descent with momentum (GDM), and resilient back propagation (RP) were used for the purpose. The Neural Network has been optimized using the MATLAB Version 7.6 Neural Network Toolbox. In the training stage, to define the output accurately, the number of neurons was increased step-by-step in the hidden layer. Inputs and outputs have been normalized in the range of (0–1) as NN works efficiently within this range. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used in hidden layer while purelinear (purelin) transfer function has been used in output layer. After the successful training of the network, the network was tested with the test data. Using the results produced by the network, statistical methods have been used to make comparisons.

Measures of prediction performance

Using the results produced by the network, statistical methods have been used to investigate the prediction performance of NN results. To judge the prediction performance of a network, MSE, and correlation coefficient (R) between network output and network target outputs in three training, testing and validation groups were used and calculated as follows:

$$MSE = \frac{\sum_{i=1}^{n}\left((yi - \bar{yi})^2\right)}{n} \text{ (Equation 1)},$$

$$R = \sqrt{1 - \frac{\sum\left((yi - \bar{yi})^2\right)}{\sum yi^2 - \frac{\sum \bar{yi}^2}{n}}} \text{ (Equation 2)}$$

Where, yi is actual data and $\bar{yi}$ is calculated data by network. Zero is the best condition for MSE and one is the most desirable condition for R.

Results and discussion

The aim of using the Artificial Neural Network (ANN) is to test the ability to predict groundwater level fluctuation in Aghili plain, urban area of Gotvand, south-west Iran. The network has six input parameters:

Rainfall, average monthly temperature (monthly minimum and maximum), relatively humidity, discharge of irrigation canals and groundwater recharge from boundary of the study area and one output parameter: groundwater level.

The available required data to simulate groundwater were rainfall during 39 years, average monthly temperature (monthly minimum and maximum) during 39 years and discharge of irrigation canals during a10 years period. These data with one-month time step were introduced to the ANN as input. Groundwater level of plain piezometers was available for eight and half years. The groundwater recharge from eastern boundary of plain also was considered as input data to the model. By applying Darcy law and using aquifer transmissivity and slop,, groundwater recharge from boundary was calculated. The width of eastern boundary also was calculated using ArcGIS10.

To design networks, analogues output and input data of the same period with an equivalent step time were used. Training data including from October 2002 to March 2009 for all networks (6×90 input data and 5×90 output data).

To consider the efficiency of every algorithm and reach to the best desired conditions, several parameters, and variables such as number of neurons in hidden layers, percent of dividing data into the three training , testing , and validation sets , learning rate, number of repeating epochs and momentum coefficient were varied. Among these conditions, number of neurons and percent of dividing data to the three training, testing, and validation sets are more effective in changing conditions and reaching to a desired state of network than others are.

Therefore, first artificial neural network input parameters including rain, relative humidity, maximum and minimum temperature, evaporation, discharge of irrigation canals and recharge from boundaries were selected as input to the model and water levels in fifteen piezometers of the plain were selected as output and were normalized by mapminmax comment in MATLAB software. Therefore, all parameters were scaled between zero and one. Then, to increase the predicting capability of the network, the input and output data were divided into three groups region according to position of plain piezometers and hydrological characteristic such a groundwater depth, hydraulically conductivity and transmissivity(fig. 5).

Piezometers of first group located in north and center of plain. Groundwater depth in this group is low to moderate, hydraulically conductivity is moderate and transmissivity is high. Piezometers of second group located in south and southwest of plain. Groundwater depth in this group is moderate to high, hydraulically conductivity is high and transmissivity is moderate.

Piezometers of first group located in east margin of plain. Groundwater depth in this group is high, hydraulically conductivity is low and transmissivity is low.

Now, by keeping number neuron in hidden layers and using the LM algorithm, the best values of learning rate, epoch number and momentum coefficient obtained for first group of data have been evaluated (Table1). Criterion to determine best values of this conditions are maximum R in training, test and validation and minimum MSE. According to the results, the best network has two layers (N1=5, N2=4), LR=0.2, MU=0.9, Epoch=300,R-All=0.76, and MSE=0.013.

Table1: Results of training the artificial neural network with LM algorithm for the first hydrogeological group

Number Net	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE	Data Percentage
1	5	4	0.3	300	0.05	0.88	0.57	0.75	0.81	0.0228	10	60-20-20
2	5	4	0.5	300	0.07	0.87	0.64	0.76	0.81	0.024	11	"
3	5	4	0.7	300	0.1	0.82	0.775	0.775	0.8	0.017	8	"
4	5	4	0.9	300	0.2	0.83	0.66	0.84	0.76	0.013	5	"
5	5	4	0.9	700	0.4	0.9	0.65	0.786	0.736	0.052	6	"
6	5	4	0.9	1000	0.2	0.817	0.51	0.796	0.742	0.029	4	"
7	5	4	0.9	300	0.1	0.83	0.87	0.915	0.829	0.00432	7	85-7.5-7.5
8	5	4	0.9	300	0.5	0.85	0.925	0.938	0.874	0.0159	3	80-10-10

N1=number of neurons in the first hidden layer, N2= number of neurons in the second hidden layer, MU= momentum coefficient, MSE=mean square error R=correlation coefficient between network output and network target outputs in training, testing and validation, LR=learning rate.

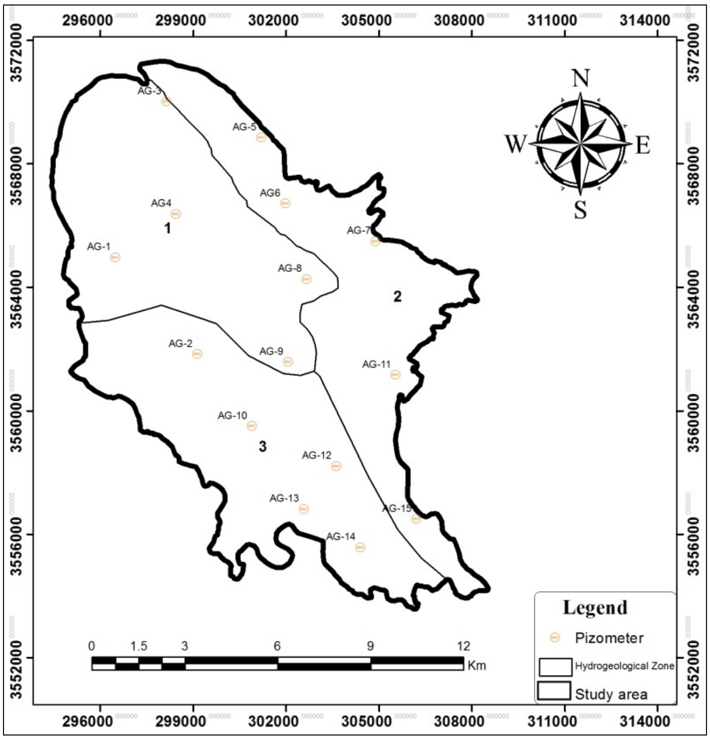

Figure 4: Piezometers position and hydrological areas in study area

Now, to reach to the best network, the percentage of data in training, testing, validation, and number of neurons in each layer were changed several times and 83 networks were produced. The detailed work is presented in (Rahmani, 2012) and only the state of the best network is presented in Table2.

After reaching to the best condition (maximum R in training, testing, validation and minimum MSE) for the network of first hydrogeological group, trained by LM algorithm, the same network was trained with algorithm GDM, SCG, and RP and their efficiencies were evaluated. Finally, the network was trained for hydrogeological group number 2 and three (Table 3 and Fig. 6).

Fig. 4 shows the comparative plot of the best networks of three hydrogeological groups that have been trained with LM, RP, SCG and GDM algorithms .In each graph number of neurons in hidden layer 1 and 2 vs. resulting MSE of network has shown. For example, network that has been trained by LM algorithm that has 10 and 11 neurons in hidden layer 1and 2, has lowest MSE. The figure also shows that networks in all hydrogeological groups that have been trained by LM algorithm have lowest MSE. The structure of the best network for three groups is 7-11-10-5, 7-13-10-5 and 6-5-6-5.

Table 2: Optimized network of first hydrogeological group, trained with LM algorithm (R-All has increased to 0.864 and MSE has decreased to 0.00795).

Group Data	Number Net	Algorithm	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE	Data Percentage
1	75	LM	11	10	0.9	300	0.5	0.845	0.957	0.942	0.864	0.00795	3	80-10-10

Table3: The best neural network for third hydrogeological group, trained with feed forward.

Group Data	Number Net	Algorithm	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE	Epoch -MSE	Data Percentage
1	1	LM	11	10	0.9	300	0.5	0.845	0.957	0.942	0.864	0.00795	3	80-10-10
	2	RP	7	4	0.9	300	0.5	0.841	0.95	0.914	0.859	0.011	5	"
	3	SCG	11	4	0.9	300	0.5	0.841	0.95	0.923	0.859	0.0116	7	"
	4	GDM	9	6	0.9	300	0.5	0.852	0.895	0.952	0.838	0.0151	13	"
2	1	LM	13	10	0.9	300	0.5	0.887	0.958	0.959	0.9	0.0055	1	"
	2	RP	5	6	0.9	300	0.5	0.886	0.969	0.926	0.898	0.0115	15	"
	3	SCG	7	4	0.9	300	0.5	0.885	0.972	0.93	0.898	0.0117	11	"
	4	GDM	5	6	0.9	300	0.5	0.79	0.92	0.92	0.81	0.017	7	"
3	1	LM	5	6	0.9	300	0.5	0.884	0.97	0.94	0.898	0.00895	3	"
	2	RP	5	10	0.9	300	0.5	0.882	0.963	0.927	0.894	0.0107	10	"
	3	SCG	13	4	0.9	300	0.5	0.882	0.962	0.941	0.896	0.01	30	"
	4	GDM	11	8	0.9	300	0.5	0.878	0.962	0.926	0.891	0.0113	126	"

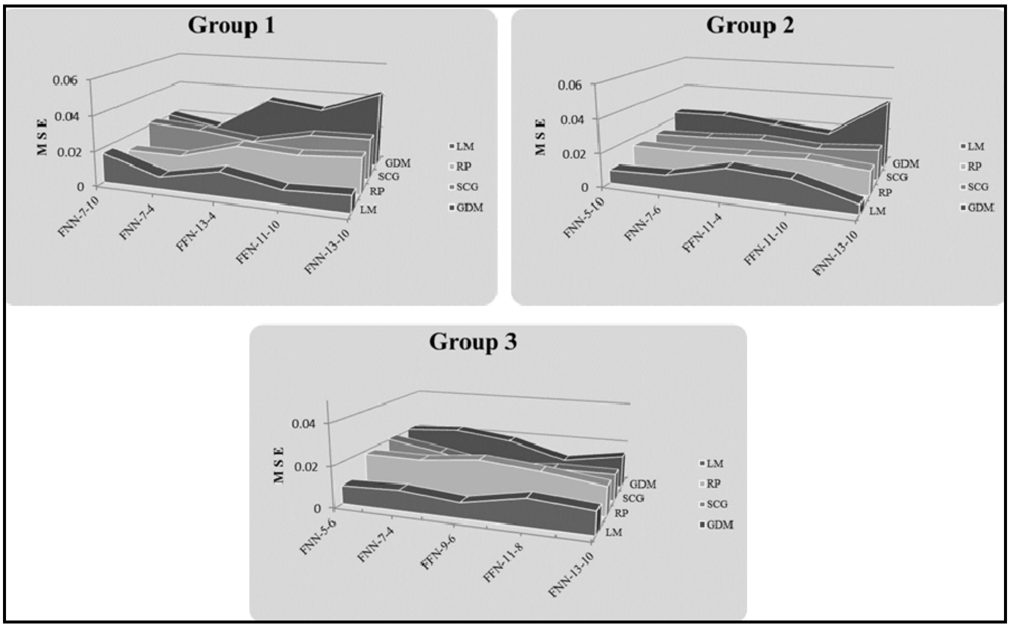

Figure 5:.Comparative plot of the best networks of third hydrogeological groups, trained with LM, RP, SCG and GDM algorithms

Verification

Now, to verify the hydrogeological groups and their neural networks, new observation data of April 2009 to January 2010 were introduced to the networks and simulated groundwater level were compared with actual groundwater of all piezometers in the study area (fig. 6, 7 and 8). As the figures show, the neural networks can simulate groundwater level accurately in most of the piezometers.

To evaluate the accuracy of the hydrogeological grouping and related designed network, a new network was designed by using all data including water level of all piezometers in the plain. The network was trained by LM algorithm. Because of high number of input data, network showed a desirable result at first training. The result was achieved where MSE= 0.00113 and R_{Train}= 0.982,

R_{Test}= 0.989, $R_{Validation}$= 0.996.The network was validated by using new data (fromMarch, 2010 to November, 2010) .The results are shown in figure 9.

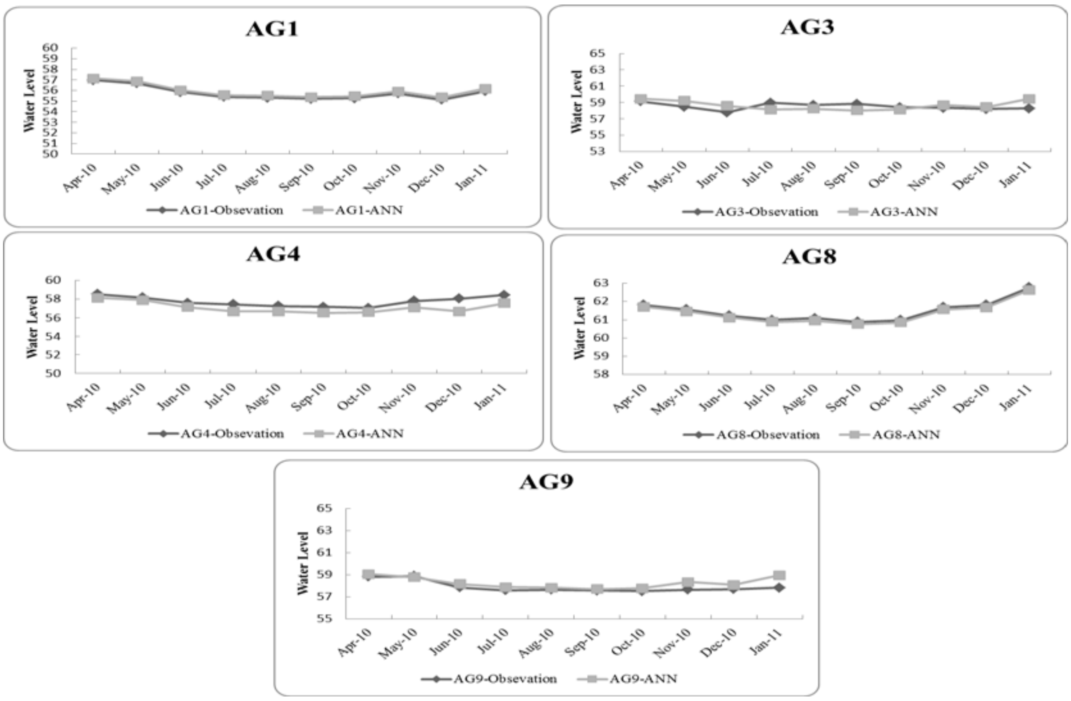

Figure 6: Variation of water table in piezometers of first hydrogeological group (simulated data and observational data)

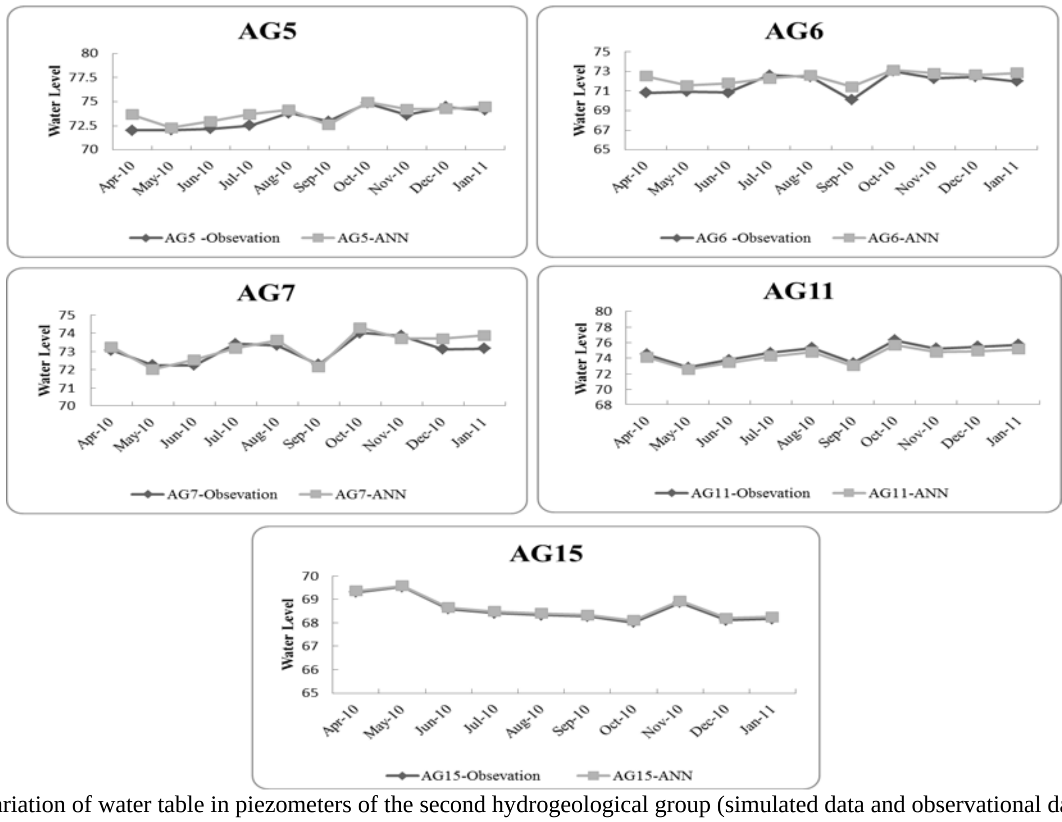

Figure 7: Variation of water table in piezometers of the second hydrogeological group (simulated data and observational data).

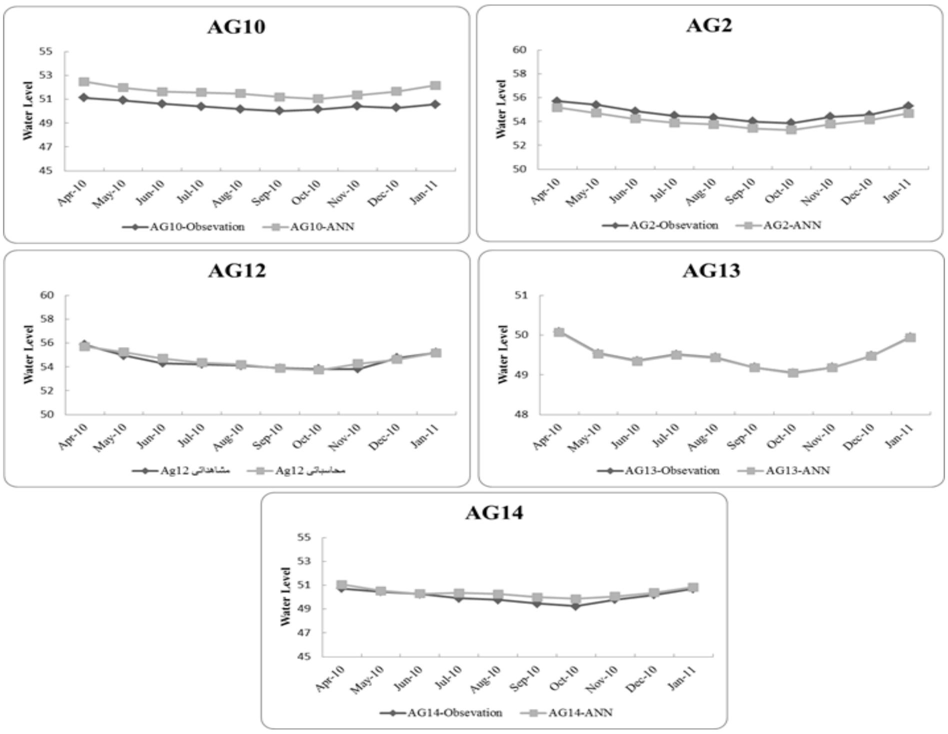

Figure8: Variation of water table in piezometers of the third hydrogeological group (simulated data and observational data)

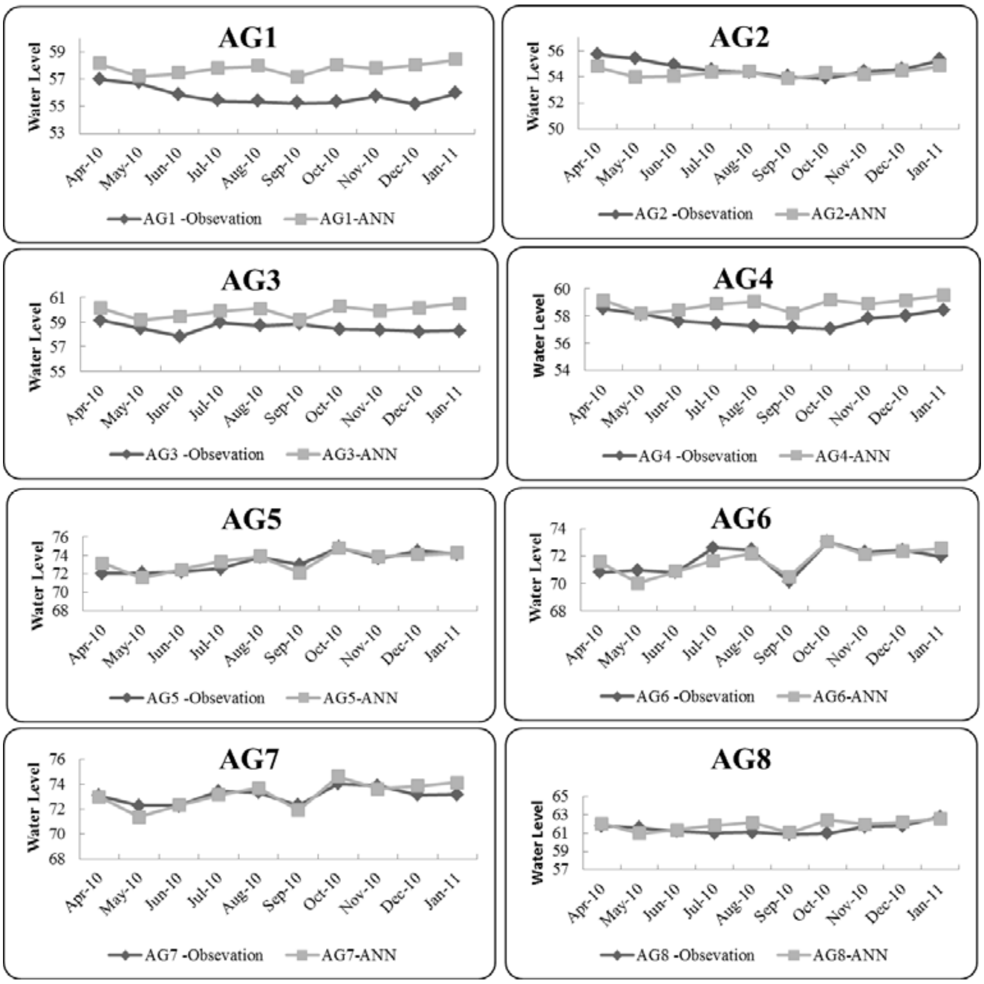

Figure 9: Variation of water table in all piezometers (simulated data and observational data)

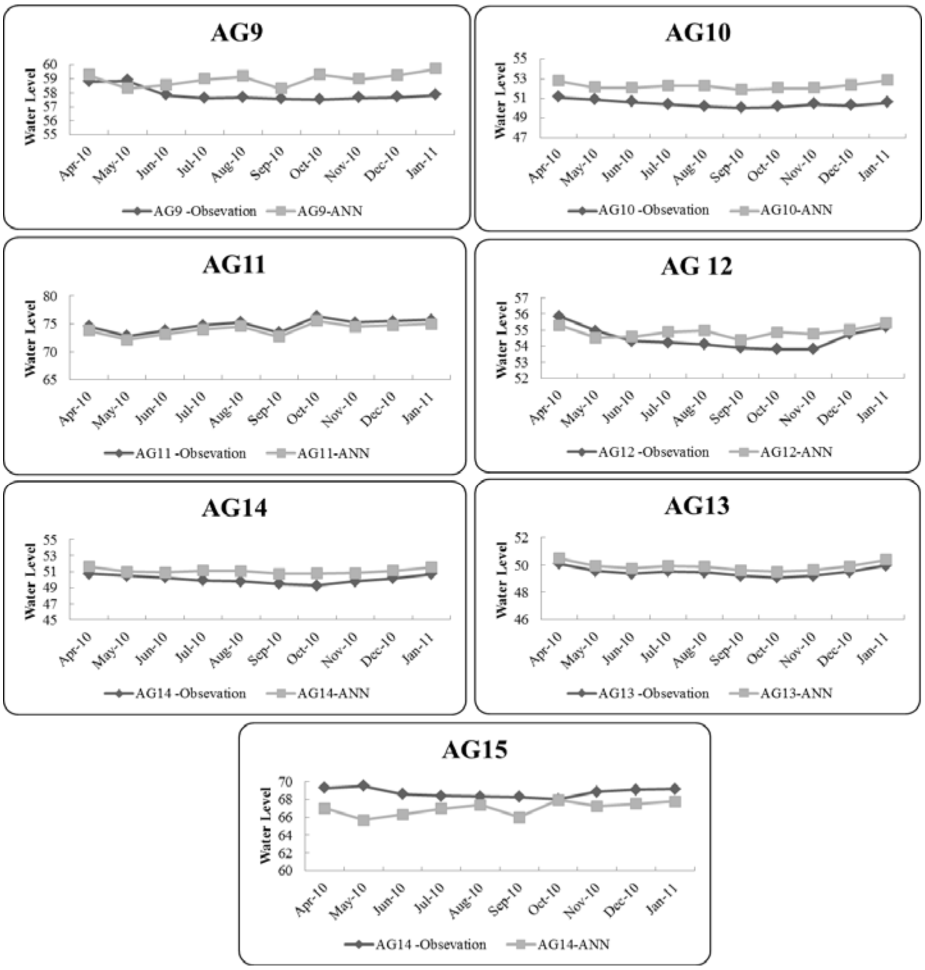

Figure 9: Continue

Figure 9 shows that, even though there is a good fit between real and calculated data in piezometers but the results are not as good as results obtained from dividing piezometers to different hydrogeological group. For example, fitting is not good in piezometer AG1, AG3, AG9, AG10 and AG15.Therefore, selecting parameters for neural network based on hydrogeological condition gives better results.

Table4: The best neural network for third hydrogeological group, trained with LM algorithm.

Number Group	Algorithm	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE	Data Percentage
1	LM	11	10	0.9	300	0.5	0.845	0.957	0.942	0.864	0.00795	3	80-10-10
2	LM	13	10	0.9	300	0.5	0.887	0.958	0.959	0.9	0.0055	1	"
1	LM	5	6	0.9	300	0.5	0.884	0.97	0.94	0.898	0.00895	3	"

Conclusion

The goal of this study was to evaluate the feed forward neural network as a possible tool for predicting groundwater level in Aghili plain aquifer, Khuzestan province, south- west Iran. Rain, evaporation, relative humidity, temperature (maximum and minimum), discharge of irrigation canal, and groundwater recharge from the plain boundary were taken as inputs, and the future groundwater levels of Aghili plain were the output. First, the available data were divided into three groups, according to hydrogeological characteristics of the plain. A back propagation (BP) neural network model with LM, GDM, RP, and SCG algorithms have been studied in two hidden layers. Number of neurons on hidden layer also varied to optimize network. Often, the best results were obtained from the LM algorithm. Base on statistical indices (R and MSE), the best networks were determined for each hydrogeological group (Table

4).These networks were trained with LM algorithm.

To verify the hydrogeological groups and their neural networks, new observation data of April 2009 to January 2010 were introduced to the networks .Then, simulated groundwater level were compared with actual groundwater of all piezometers in the study area.

Even though there was a good fit between real and calculated data by considering all piezometers but the results were not as good as results obtained from dividing piezometers to different hydrogeological group.

Therefore, the study shows that training the artificial neural network with respect to hydrogeological regions gives better results.

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