JOURNAL GEOLOGICAL SOCIETY OF INDIA
Vol.85, January 2015, pp.98-106

Forecasting Groundwater Level by Artificial Neural Networks as an Alternative Approach to Groundwater Modeling

MANOUCHEHR CHITSAZAN[1], GHOLAMREZA RAHMANI[2] and AHMAD NEYAMADPOUR[3]
Faculty of Earth Sciences, Ahvaz, Shahid Chamran University, Iran
Email: [1]M_Chitsazan@scu.ac.ir; [2]Gholamreza90@yahoo.com. [3]Anpour@gmail.co

Abstract: The main purpose of this article is to apply feed forward back propagation neural network (FNN) to predict groundwater level of Aghili plain, which is located in southwestern Iran. An optimal design is completed for the two hidden layers with four different algorithms: descent with momentum (GDM), Levenberg Marquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG). The training data for ANN is obtained from observation data. Rain, evaporation, relative humidity, temperature, 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. Statistical analysis in terms of Mean-Square-Error (MSE) and correlation coefficient (R) was used to investigate the prediction performance of ANN. FFN-LM algorithm has shown best result in the present study for all three hydrogeological groups. Now, to predict water level, the t time data (October 2003 to July 2009) and t+1 time data (October 2004 to July 2010) were used as input and output respectively. The best condition of this network was achieved for each group of data. Next, with defining the new input data related to August 2010 to January 2011 groundwater level was predicted for the following year. The achieved results of ANN model in contrast with results of finite difference model showed very high accuracy of artificial neural network in predicting groundwater level.

Keywords: Artificial neural network, Feed forward back propagation, Groundwater, Aghili plain, Iran.

INTRODUCTION

Groundwater is always an important resource for supply of drinking and agriculture 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 for different users (Firouzkouhi, 2011). Groundwater reservoir (aquifer) is a complicated system that is faced with either natural or unnatural factors caused from human activity. These factors affect the aquifers at different chronological levels that lead to groundwater fluctuations. Thus, to exploit and manage groundwater, models are needed to predict groundwater level fluctuations. Nowadays, mathematical models simulated by cmputer technology are used in exploiting groundwater. However, the goodness of the model used depends on the input data since many factors are involved in groundwater balance, exact estimation of groundwater fluctuation rate is a challenging task. Artificial neural networks (ANN) can help in solving such problems. A neural network consists of many non-linear computational elements operating in parallel and arranged in patterns resembling those of biological neurones. ANN is especially useful if nonlinearity exists in a problem domain (Taslloti, 2004). Many works on hydrogeology have used artificial neural networks as a research tool. Aziz and Wong (1992) used artificial neural networks for the first time to determine aquifer parameters. Based on the ability of artificial neural network in defining processes and patterns they trained the ANN by using parameters such as groundwater drawdown and obtained transmissivity, storage coefficient and ratio of observation well distance from pumping well to aquifer thickness. To train the model by BP (Back Propagation) algorithm, they used supervised training and by a three-layer network modeled – two unconfined and a leaky aquifer. The predicted parameters were compared with results obtained from old and traditional methods like Theis and Jacob. Coulibaly et al. (2001) calibrated three types of artificial neural network models by using data of groundwater level and hydrometeorology to simulate the groundwater fluctuation in Gondo aquifer. In this study, four kinds of ANN structures PNN (probabilistic neural network), GRBF (generalized RBF model), RNN (globally recurrent neural network), and IDNN (Input delay neural network) were used for simulation. The results of the IDNN and the PNN were almost same despite their different learning procedure but the GRBF performed poorly compared to the other models. Finally, the simulation showed that RNN is the most suitable model when calibration period is shorter than seven years. Coppola et al. (2003) showed that artificial neural network has a high ability to predict accurately the groundwater level fluctuations in an unsteady state of an aquifer influenced by pumping and different weather condition. It is also shown that ANN models are good in simulating karstic and leaky aquifers where other numerical models are unacceptable in such domains. Maier and Dandy (2000) have also presented comprehensive reviews on the applications of ANN in hydrology. Esmaili Varaki (2003) has presented an intelligent model for estimating the fluctuation of alluvial aquifer groundwater level by using artificial neural network. For the first time, artificial neural networks were used for evaluating dynamic water level in karstic aquifer by Lallahem et al. (2005). They used a MLP network and focused on simulation of hydraulic head change at an observation well in the area. However, their results showed that there is a need for exact knowledge of pumping from each well in karstic aquifers, as it is difficult to simulate the sudden drop and rises. Also Ioannis et al. (2010) used neural network for karstic aquifers. Despite this, the ANN is still a useful tool to simulate karstic aquifers that are difficult to simulate by numerical groundwater models. Uddameri (2006) used statistical and artificial neural network models to forecast potentiometric levels at a deep well in South Texas. Shaoyuan et al. (2007) simulated the effects of hydrological, weather and humidity conditions on groundwater level by neural networks in lower part of Shenyang river basin, northwest of China. The ANN model was able to predict groundwater level with the average error of 0.37 or lower with high accuracy. Steyl (2009) reviewed the application of artificial neural networks algorithms in geohydrology. Sreekanth et al. (2009) examined function of artificial neural network model (standard neural network) trained by LM algorithm to predict fluctuation of groundwater level in the basin of Maheshwaram, Hyderabad, India. They measured the model efficiency and accuracy based on the root mean square error (MSE) and regression coefficient (R). The model provided the best fit and the predicted trend followed the observed data closely (MSE = 4.50 and R2 = 0.93). They inferred that ANN appears to be a promising tool for precise and accurate groundwater level forecasting. Rosmina (2007) evaluated neural network for level forecasting in Bedup river. Nadiri (2007) evaluated artificial neural network ability in modeling complex aquifer of Tabriz and predicted water table of aquifer in a central piezometer and related the best result to feed forward back propagation artificial neural network trained by LM algorithm. Using the structure, he also predicted groundwater levels of eight chosen piezometers in the study area. Mirarabi (2008) and Rezaee et al. (2008) also approached neural network in earth sciences in Iran. Also Gidson (2010) applied artificial neural network in geohydrology.

The main purpose of this article is to use artificial neural networks especially feed forward back propagation neural networks to simulate and predict groundwater level and to compare the results with finite differences model results that are proposed for the study area.

MATERIALS

Case Study: Alluvial Plain Aquifer in Southwest Iran

The study area is part of Aghili plain that is located in northeast Khuzestan province, Iran (Fig.1). Statistical data shows that annual average rainfall in 39 years is 404.81milimeters and in 2010-2011 is 330 millimeters. Aghili is an alluvial plain that was deposited by Karun river (Nejati Jahromi, 2009). Aghili plain has arid and dry climate.

METHODS

Selection of a Suitable Neural Network Model

Neural network design is a multipart and tough task, as there is much possible architecture available and important decisions are essential to set up an appropriate and stable network. First, an appropriate neural network is selected, based on physical knowledge of the problem. In this study, neural network is supposed to predict groundwater in Aghili plain and a neural network will be selected according this task. A few neural network models can be used in prediction. However, a back propagation network was selected because it is a powerful learning model and it does not require prior knowledge of the relationships between input and output and its learning algorithm has been well developed. The back propagation model is a multilayered, feed forward network with supervised learning. The term back propagation refers to the backward propagation of an error signal through the network. In this study, the artificial neural network contains three layers, input, hidden, and output layers (Fig.2). During the training phase, the training data is fed into the input layer. The data is propagated to the hidden layer and then to the output layer. This is called the

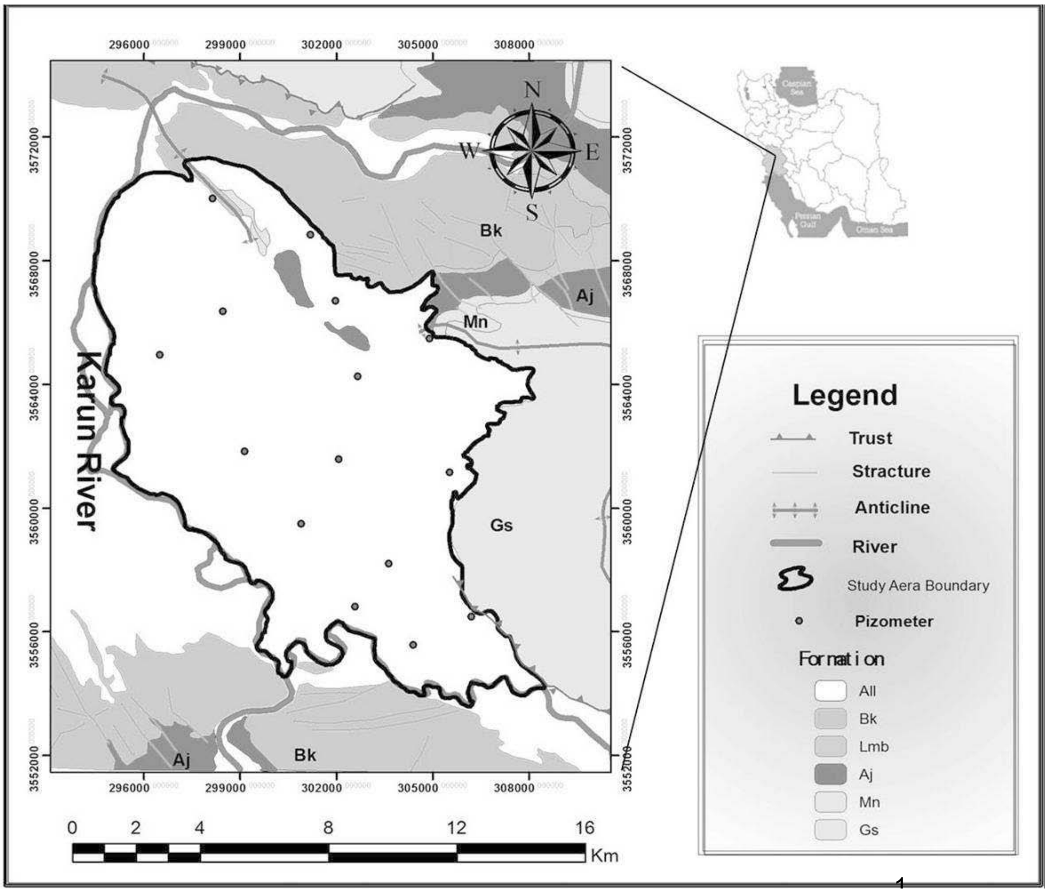

Fig.1. Geological map of study area and observation well location.

forward pass of the back propagation algorithm. In forward pass, each node in hidden layer gets input from all the nodes from input layer, which are multiplied with proper weights and then added. The output of the hidden node is the nonlinear transformation of the resulting sum. Similarly, each node in output layer gets input from all the nodes from hidden layer, which are multiplied with appropriate weights and then summed. The output of this node is the non-linear transformation of the resulting sum (Nazari and Ersoy, 1992; Menhaj, 2008).

Development of the Neural Network Model

To develop ANN, the neural network toolbox from the Mathwork, Inc. (Demuth and Beale, 2006) was used. This toolbox runs under the Mathworks' MATLAB program and provides the capability to design many different types of neural systems for a variety of application.

Success in designing a neural network depends on a clear understanding of the problem (Nelson and Illingworth, 1991). Knowing which input variables are important in the groundwater fluctuation is critical, though this task is not easy. However, hydrogeological knowledge can help in choosing variables which are probable important forecasters. Available hydrological and hydrogeological data in the study area are: rainfall during 39 years, average monthly temperature (monthly minimum and maximum) during 39 years and discharge of irrigation canals during 10 years period. The groundwater recharge from eastern boundary of the plain was also considered as input data to the model. 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.

Data Collection

The climatologically data (rainfall during 39 years), average monthly temperature (monthly minimum and maximum) during 39 years were obtained from local climatological center in the study area. Groundwater data and discharge of irrigation channels were obtained from Khuzestan water and power organization. Groundwater from eastern boundary was calculated from Darcy formula.

Data Preprocessing

Data preprocessing was carried out for analyzing and

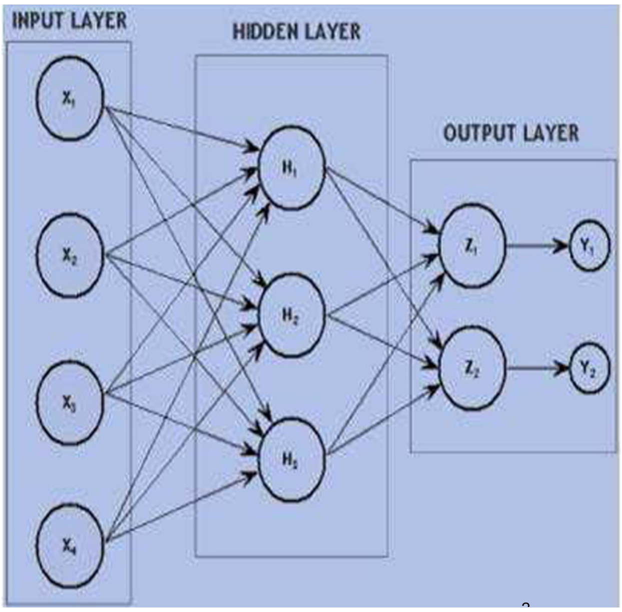

Fig.2. Structure of back propogation model in neural networks.

transforming the input and output variables to minimizing noise, highlight important relationships, detect trends, and flatten the distribution of the variable to help the neural network in learning the relevant patterns (Kaastra and Boyd, 1996). The raw data were also scaled between zero and one.

Model Design

Number of Hidden Layers and Neurons

There are a countless number of ways to construct a neural network. Neurodynamic and architecture are two terms used to express the way in which a neural network is structured. The combination of neurodynamic and architecture describe the network paradigms. The number of input nodes in the input layer was taken equal to the number of input variables. Since no guideline is yet available on the number of hidden nodes of the hidden layer (Vemuri, 1992), these were initially tried from the physical knowledge of the problem and statistical analysis. Thus, different combinations of antecedent values of the time series were considered as input nodes. The output node is the time series data to be predicted in one-step ahead. For deciding the optimal hidden neurons, a trial and error procedure started with two hidden neurons initially, and the number of neurons in hidden layers was increased up to 10.

Training, Testing and Validation Sets

Accepted practice is to divide the available data into three distinct sets namely the training, testing, and validation sets. As the training set is used by neural network to learn the patterns present in the data, 80 % of data were allocated to the training set, 10 % to testing set and 10 % to validation set.In the current study, we select the networks, which performed best on the testing set, and a final check on the performance of the trained network was made using the validation set.

Evaluation Criteria

To assessing the network, statistic criterions such as R and MSE between output and network desired goal in three training group, validation and test were used which were calculated according to the following equivalents:

$$MSE = \frac{\sum_{i=1}^{n} (yi - \overline{yi})^2}{n} \qquad \text{(eq 1)}$$

$$R = \sqrt{1 - \frac{\Sigma\ (yi - \overline{yi})^2}{\Sigma yi^2 - \frac{\Sigma \overline{yi}^2}{n}}} \qquad \text{(eq 2)}$$

Where, yi are actual data and $\overline{yi}$ are calculated data by network. Zero is the best condition for MSE and one is the most desirable condition for R. Therefore, among the trained networks for each of related data groups regarding to above criterion, the best network was selected.

Neural Network Training

Training is a technique used to minimize the error of a network. The network weights are adjusted until the error is at a minimum or a predefined limit has been achieved (Durrant, 2001).

Learning Strategy

We implemented a feed-forward multilayer artificial neural network with a back-propagation training descent with momentum (GDM), Levenberg marquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG).

The LM algorithm provided the best performance, and has been shown to be fast and highly efficient when training small and medium size networks, especially when high precision is required. The LM method combines the Gauss-Newton method, which converges quickly near the minimum, and the gradient descent method, which converges in all space but relatively slow.

Activation Function

The sigmoid function was assigned as the activation in the hidden layer and the linear function was used in the output layer. The sigmoid function is commonly used in back propagation.

Stopping Criteria

Network training would be ended based on the cross-validation stop criteria to avoid the tendency of the neural network to over fit the training data. The mean squared error (MSE) was selected as the main criterion to measure performance of the model because it is very sensitive to even small difference of model performance (Murrells, 2008).

RESULT 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, southwest Iran. The network has following input parameters: Rainfall, relative humidity, average monthly minimum temperature, average monthly maximum temperature, discharge of irrigation canals and groundwater recharge from boundary of the study area and one output parameter, groundwater level. The available 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 10 years period. 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 the plain was also considered as input data to the model. 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. To design network, analogues output and input data of the same period with an equivalent step time were used. Therefore, according to available data of water level in piezometers, the other data, from October 2002 to January 2011, were selected. 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 than others. Therefore, first artificial neural network input parameters including rain, relative humidity, maximum and minimum temperature, evaporation, discharge of irrigation canals, recharge from boundaries and groundwater levels of all piezometers were selected as input to the model and water levels in fifteen piezometers of the plain were selected as output and were normalized. Therefore, all parameters were scaled between zero and one.

Designing the Network According to Hydrogeology of the Study Area

To increase the predicting capability of the network, the input and output data were divided into three groups, according to position of plain piezometers and hydrological characteristic such a groundwater depth, hydraulically conductivity and transmissivity.Now, by keeping all condition the same and using the LM algorithm, the best values of learning rate, epoch number and momentum coefficient were obtained for first hydrogeologic group of data. Preliminary run showed that optimum networks can be obtained with the following parameters given in Table 1.

Table1. Results of training the artificial neural network with LM algorithm for the first hydrogeologic group

Number Net	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE (all data)	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	60-20-20
3	5	4	0.7	300	0.1	0.82	0.775	0.775	0.8	0.017	8	60-20-20
4	5	4	0.9	300	0.2	0.83	0.66	0.84	0.76	0.013	5	60-20-20
5	5	4	0.9	700	0.4	0.9	0.65	0.786	0.736	0.052	6	60-20-20
6	5	4	0.9	1000	0.2	0.817	0.51	0.796	0.742	0.029	4	60-20-20
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	0.95	0.925	0.938	0.874	0.0159	3	80-10-10
9	5	-	0.9	300	0.2	0.942	0.92	0.9	0.856	0.0117	12	80-10-10
10	5	-	0.9	300	0.2	0.949	0.919	0.9	0.861	0.0205	7	80-10-10

Number of epochs = 300, learning rate = 0.5, coefficient of momentum = 0.9 and dividing percentage of data = 80% (training), 10% (validation) and 10% (testing).
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 three training, testing and validation, LR = learning rate.

Table 2. the best state training by feed forward neural network for each group data in modeling.

Group Data	Number Net	Algorithm	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE (all data)	Epoch-MSE	Data Percentage
1	1	LM	11	10	0.9	300	5.0	945.0	957.0	942.0	964.0	00795.0	3	80-10-10
	2	RP	7	4	0.9	300	0.5	0.941	0.95	0.914	0.959	0.011	5	80-10-10
	3	SCG	11	4	0.9	300	0.5	0.941	0.95	0.923	0.959	0.0116	7	80-10-10
	4	GDM	9	6	0.9	300	0.5	0.952	0.895	0.952	0.938	0.0151	13	80-10-10
2	1	LM	13	10	0.9	300	0.5	0.987	0.958	0.959	0.9	0.0055	1	80-10-10
	2	RP	5	6	0.9	300	0.5	0.986	0.969	0.926	0.998	0.0115	15	80-10-10
	3	SCG	7	4	0.9	300	0.5	0.985	0.972	0.93	0.998	0.0117	11	80-10-10
	4	GDM	5	6	0.9	300	0.5	0.89	0.92	0.92	0.91	0.017	7	80-10-10
3	1	LM	5	6	0.9	300	0.5	0.984	0.97	0.94	0.998	0.00895	3	80-10-10
	2	RP	5	10	0.9	300	0.5	0.982	0.963	0.927	0.994	0.0107	10	80-10-10
	3	SCG	13	4	0.9	300	0.5	0.982	0.962	0.941	0.996	0.01	30	80-10-10
	4	GDM	11	8	0.9	300	0.5	0.978	0.962	0.926	0.991	0.0113	126	80-10-10

Now, keeping the mentioned parameters constant, number of reruns in hidden layers were optimized for three hydrogeologic groups, using four learning algorithms(LM, RP, SCG, GDM). Table 2 shows the results of training by LM algorithm and it gives the best results for all three hydrogeologic groups. For example, optimum network for first hydrogeologic group that has been trained by LM algorithm (first row) has the highest R_{all}=0.964 and the lowest MSE=0.00795. In addition, the optimum network for second hydrogeologic group that has been trained by LM algorithm has the highest R_{all} =0.9 and the lowest MSE=0.0055. Moreover, optimum network in third hydrogeologic group that has been trained by LM algorithm has the highest R_{all}=0.998 and the lowest MSE=0.00895. Thus, these optimum networks are selected for groundwater level forecasting in Aghili plain.

The network with two hidden layers of 11 and 10 hidden neurons was selected for the first hydrogeologic group. The network with two hidden layers of 13 and 10 hidden neurons was selected for second hydrogeologic group. The network with two hidden layers of 5 and 6 hidden neurons was selected for third hydrogeologic group.

Forecasting using Artificial Neural Networks

Artificial Neural Networks (ANNs) are being applied to a wide range of practical problems. ANN are not programmed but learn by example (McCluskey, 1997), and are used in such problems as hydrological and hydrogeological predictions. Once a network is trained it may be used to produce forecasts. In multivariate forecasting, the number of inputs is determined by the number of indicators (controlling factors) used. If the output variable is also an input variable, new input vectors must be prepared one at a time and presented to the network to produce the next forecast in the iteration (Paris,2008). Table 3 shows the typical process.

In this study, a feed-forward network with back-propagation algorithms was used to predict the groundwater level of a plain. The trained network with minimum error was saved and used for predicting future price value. The neural network of each hydrogeological group producing minimum value of MSE was selected as best network and further used in one-year-ahead water level forecasting of groundwater. Out of the different configurations tested, the following networks were selected.

The optimized networks were trained forecasting. Input parameters are rain, relative humidity, maximum and minimum temperature, evaporation, discharge of irrigation canals, recharge from boundaries and output parameters are groundwater levels of all piezometers. Various combinations of inputs, which are input values in different times, are experimented for feeding into the ANN. Inputs are values of aforementioned variables in times t, t-1, t-2 and the goal is to forecast the water level value in time (t+1). Thus, according to Table 3, data of October 2002 to July 2009 were introduced as input and data of October 2003 to July 2010 were introduced as output to the network.Therefore, finding the best relationship between the input data of current year and the output (of groundwater level) data of next year is gained through training. Therefore, after training, the optimized network can predict the next year groundwater level. Table 4 shows the optimized parameters of three

Table 3. Steps in forecasting using a neural network forecasting model (Paris,2008)

Step 1:	Present t input vector to the network to produce t+1 output value
Step 2:	De-scale t+1 output value
Step 3:	Use de-scaled t+1 output value to calculate related input
Step 4:	Normalize input variables
Step 5:	Prepare t+1 input vector
Step 6:	Present t+1 input vector to the network to produce t+2 output values, etc.

Table 4. the optimized networks after training for forecasting

Hydrogeological Groups	N1	N2	MU	Epoch	LR	R-Train	R-Validation	R-Test	R-All	MSE (all data)	Epoch-MSE	Percentage Data
1	11	8	0.9	300	0.1	0.97	0.963	0.945	0.932	0.00582	6	80-10-10
2	7	8	0.9	300	0.1	0.987	0.963	0.942	0.956	0.00498	1	80-10-10
3	5	4	0.9	300	0.1	0.957	0.956	0.976	0.958	0.0089	17	80-10-10

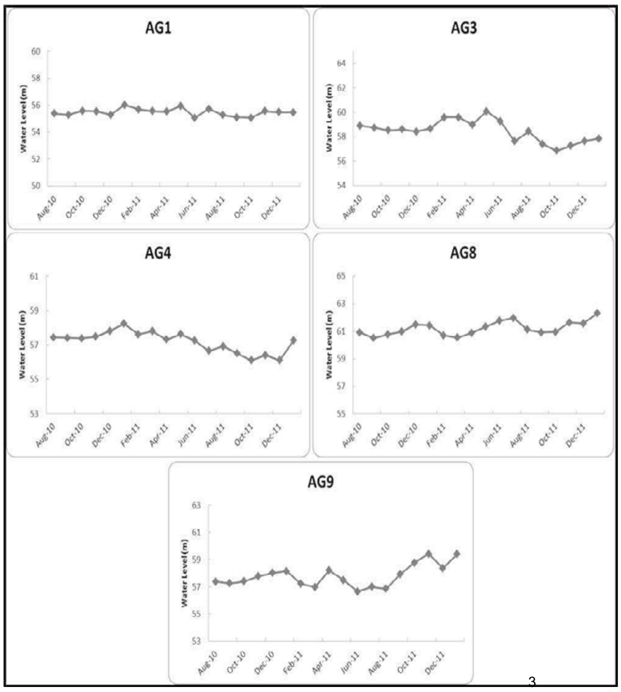

Fig.3. Results of prediction model for first group of observation well data.

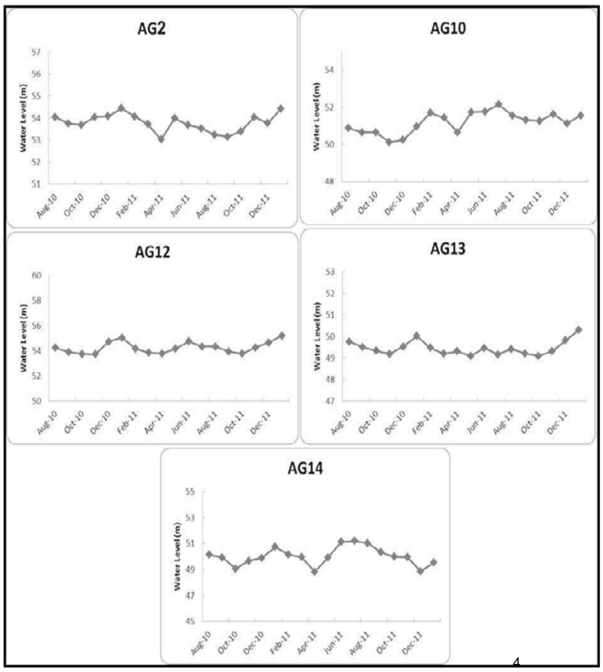

Fig.4. Results of prediction model for second group of observation well data.

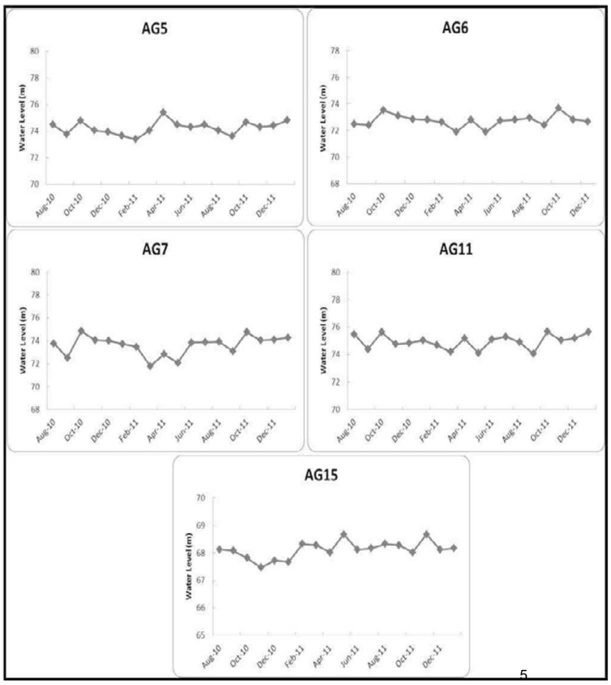

Fig.5. Results of prediction model for third group of observation well data.

trained networks, each belonging to one hydrogeologic group.

Then, by using these networks and introducing the related new input data of August 2009 to January 2010, simulation was done and groundwater level in the same months in the next year (August 2010 to January 2011) was predicted (Figs. 3, 4 and 5).

Comparing the ANN's Results with Finite Differences Model

In the study area, a finite difference model also has been developed for predicting groundwater level in Aghili plain (Firozkohi, 2010). Therefore, the accuracy of the ANN model can be quantified by comparing it with finite difference model. Within this context,the results of mathematical model were compared with the achieved results of predicting groundwater level by neural network.

Groundwater level was predicted for period of October 2008 to September 2012 by the finite difference model but

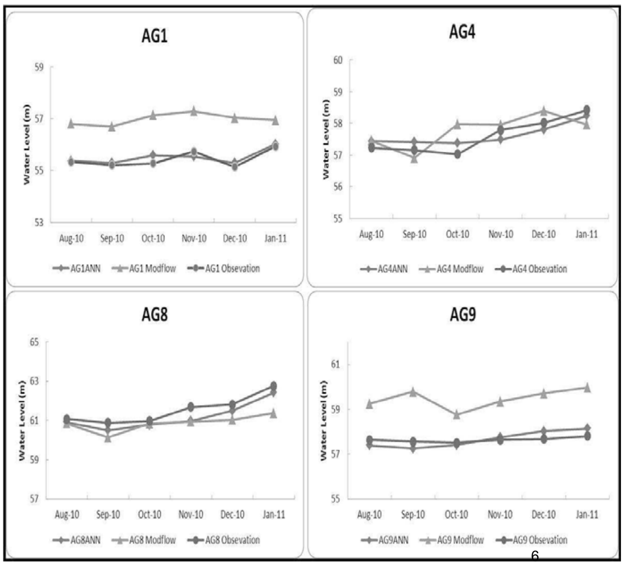

Fig.6. Comparison of prediction results with ANN and finite difference models with observation data for the first group of observation well.

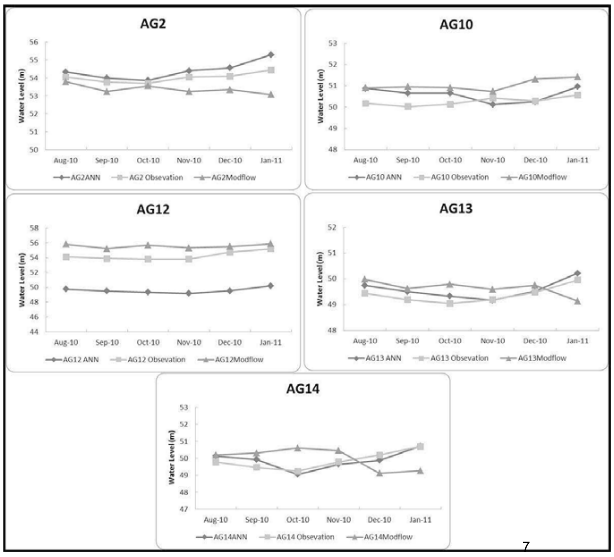

Fig.7. Comparison of prediction results with ANN and finite difference models with observation data for the second group of observation well.

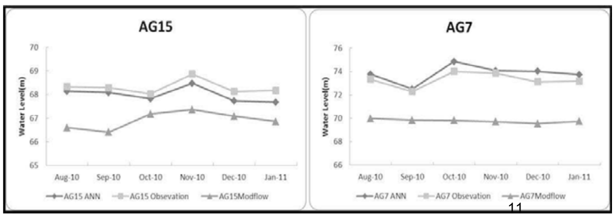

Fig.8. Comparison of prediction results with ANN and finite difference models with observation data for the third group of observation well.

ANN only predicted the groundwater level for period of August 2010 to January 2011. Therefore, comparison of predicted groundwater levels with observation data was performed for period August 2010 to January 2011 for two models (Figs. 6, 7 and 8).

The plots show that the predicted groundwater levels by artificial neural network mode in all piezometers approximately are fitted with observation data better than the finite difference model.

CONCLUSION

In this article, the applicability of artificial neural network of feed forward back propagation in predicting groundwater level was tested. First, the input and output data were divided into three hydrogeological groups and for each of them a network with two hidden layers was trained, using LM, SCG, RP and GDM training algorithms. The results showed that LM algorithm has the best performance for training all three hydrogeological groups.

After designing the best network for each hydro-geological group and verifying their capabilities in simulating groundwater in Aghili plain,the same networks were trained for groundwater prediction. Input parameters like rain, relative humidity, maximum and minimum temperature, evaporation, discharge of irrigation canals, recharge from boundaries and groundwater levels of all piezometers, in times t, t-1, t-2 and the water level value in time (t+1) were fed to the networks.

The results showed that, the ANN model is able to predict the complex response of the physical system that is simulated.

References

Aziz, A.R.A. and Wong, K.F.V. (1992) Neural network approach the determination of aquifer parameter. Groundwater, v.30(2), pp.164-166.

Copola, E., Szidarovszky, F., Poulton, M. and Charls, E. (2003) Artificial neural network approach for predicting transient water levels in multilayered groundwater system under variable state, pumping, and climate conditions. Jour. Hydro. Engg., v.8(6), pp.348-380.

Coulibaly, P., Anctil, F., Aravena, R. and Bobe´e, B. (2001) ANN modeling of water table depth fluctuations. Water Resources Res., v.37(4), pp.885–896.

Demuth, H. and Beale, M., Neural Network Toolbox User's Guide. For use with MATLAB, The MathWorks Inc, (file:/sw/matlab/help/fulldocset.html from Unix workstations).

Durrant, P.J. (2001) WinGammaTM : a non-linear data analysis and modelling tool for the investigation of non-linear and chaotic systems with applied techniques for a flood prediction system. PhD thesis. Department of Computer Science, Cardiff University.

Esmaili Varaki, M. (2003) Presenting an intelligent model for estimating the fluctuation of alluvial aquifer groundwater level by using artificial neural network. the collection of first two yearly conference of managing water resources of Iran.

Firouzkouhi, R. (2011) simulating groundwater resources of Aghili-Gotvand plain by using mathematical model of finite differences. Dissertation, Shahid Chamran University of Ahwaz, Iran.

Gidson, S (2009). Application of Artificial Neural Networks in the Field of Geohydrology. Thesis for Msc of University of the Free State.

Ioannis, C., Trichakis, Ioannis, K., Nikolos, G. and Karatzas, P. (2009) Artificial Neural Network (ANN) Based Modeling for Karstic Groundwater Level Simulation. Water Resourses Management, Springer.

Kaastra, I. and Boyd, M. (1996). Designing a neural network for forecasting financial and economic time series. Neurocomputing, v.10(3), pp.215-236.

Lallahem, S., Manina, J., Hani, A. and Najjar, Y. (2005)on the use of neural networks to evaluate groundwater levels in fractured porous media. Jour. Math. Computer Modell., v.37, pp.1047-1061.

Maier, H.R. and Dandy, G.C. (2000) Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications. Environ. Modell. Software, v.15, pp.101–124.

McCluskey, W.J. (1997). A critical review of computer assisted mass appraisal techniques. Computer Assisted Mass Appraisal: An International Review.WJMcCluskey and AS Adair. Aldershot, Ashgate, pp.1-25.

Menhaj, M.B. (2008) Fundamental of neural network, first volume, first established, established of Industrial Amir Kabir University, Tehran, Iran.

Mirarabi, A. (2008) Predicting the fluctuation of groundwater level of Birjand plain by using artificial neural networks. Dissertation, Tarbiat Moalem University of Tehran, Iran.

Murrells, C.M. (2008) Twist Liveliness of Spun Yarns and the Effects on Knitted Fabric Spirality. PhD thesis of Stuart David Paris. The Hong Kong Polytechnic University.

Nadiri. A. (2007) Predicting groundwater level surrounding Tabriz city. Mse thesis of hydrogeology. Dissertation, Tabriz University, Iran.

Nazari, J. and Ersoy, O. (1992). Implementation of Back Propagation Neural Networks with Matlab, School of Electrical Engineering – Purdue University, West Lafayette, Indiana,

Nejati Jahromi, Z. (2009) simulating groundwater resources of Aghili plain by using mathematical model of finite differences. Dissertation, Shahid Chamran University of Ahwaz, Iran.

Nelson, M.N. and Illingworth, W.T. (1991) A practical guide to neural nets. Addison-Wesley Publishing Company, Reading, MA.

Paris, S.D., Ware, J.A., Jenkins, D.H. and Wilson, I.D. (2001) Adding Value to Desktop Valuations: The Use of Artificial Intelligence Techniques to Assist in Residential Property Price Forecasting. The Cutting Edge, RICS.

Rezaee, M.R., Kadkhodaie-Ilkhchi, A. and Alizadeh, P. M. (2008) Intelligent approaches for the synthesis of petrophysical logs. Jour. Geophys. Engg., v.5, pp.12–26.

Rosmina, B., Nabil, B., Charles, B. and Suhaila, S. (2007) Artificial Neural Network for Precipitation and Water Level Predictions of Bedup River. IAENG International Jour. Computer Sci., 34:2, IJCS_34_2_10.

Shaoyuan, F., Shaozhong, K., Zailin, H., Shaqiun, C. and Xiaomin, M. (2007) Neural Networks to Simulate Regional Ground Water Levels Affected by Human Activities. Groundwater, v.46(1), pp.80-90.

Sreekanth, P.D., Geethanjali, N., Sreedevi, Shakeel, A., Ravi Kumar, P.D., Kamala, N. and Jayanthi, P.D. (2009) Forecasting groundwater level using artificial neural networks. Curr. Sci., v.96(7), pp.933-939.

Steyl, G. (2009) Application of Artificial Neural Networks in the Field of Geohydrology, University of the Free State, South Africa.

Taslloti, B. (2004) Estimating groundwater level by using MODFLOW and artificial neural network, Msc thesis of irrigation and drainage engineering, Tarbiat Modares University of Tehran, Iran.

Uddameri, V. (2006) Using statistical and artificial neural network models to forecast potentiometric levels at a deep well in South Texas. Environ. Geol., v.51, pp.885–895.

Vemuri, V.R. (1992) Artificial Neural Networks, Concepts and Control Applications, IEEE Computer Soc. Pr., Los Alamos, California.

(Received: 7 January 2013; Revised form accepted: 7 June 2013)