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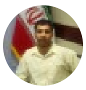
Mohammad Mirzavand
University of Kashan


M. Akbari
University of Kashan


Hanifreza Motamed Shariati
University of Tehran

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Groundwater level fluctuation forecasting using artificial neural network in arid and semi-arid environment

Mohammad Mirzavand[a]*, Seyyed Javad Sadatinejad[b], Hoda Ghasemieh[c], Mahmud Akbari[d], Hanifreza Motamed Shariati[e]

[a] Ph. D Candidate, University of Kashan, Kashan, Iran
New Sciences and Technologies Faculty , University of Tehran, Tehran, Iran
[c] Dept. of Watershed Management, , University of Kashan, Kashan, Iran
[d] Dept. of Civil Engineering, University of Kashan, Kashan, Iran
[e] Ph. D Candidate, University of Tehran, Tehran, Iran

Corresponding author: mmirzavand@grad.kashanu.ac.ir

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Abstract

In arid and semi-arid environments, groundwater plays a significant role in the ecosystem. In the last decades, groundwater levels have decreased due to the increasing demand for water, weak irrigation management and soil damage. For the effective management of groundwater, it is important to model and predict fluctuations in groundwater levels. In this study, groundwater table in Kashan plain aquifer forecasted using Artificial Neural Networks. MLP and RBF models were used to simulate the ground water table, but, because of the high number of wells studied, the samples were first organized into 5 clusters based on a Vard cluster analysis algorithm. The results indicated that, for all clusters, MLP showed good precision for predicting water depth in 37 months ahead. The correction coefficient within clusters 1, 2, 3, 4, and 5 were, respectively, 0.86, 0.88, 0.93, 0.55, and 0.79. The results showed that by change of data, education algorithm and transport function; the model can be changed into the best. In 60, 20 and 20 percent of models, Delta-Bar-Delta, Momentum and Levenberg-Marquardt were best Education Algorithm, respectively. In 60, 20 and 20 percent of models hyperbolic tangent Axon, Sigmoid Axon and Linear hyperbolic tangent Axon were best transport function, respectively.

Keywords: Artificial Neural Network, Groundwater fluctuation, Kashan aquifer, MLP, RBF.

1. Introduction

Groundwater is a precious resource that is accessed via wells for agriculture, home, and industrial use as given by Affandi and Watanabe (2007). As mentioned by Todd and Mays, the use of ground water is increasing because of its easy availability, low cost, and high quality (Todd and Mays 2005). Surface water accounts for 3% of the total freshwater while groundwater comprises as much as 30% of freshwater worldwide (Gleick 1993). Currently in Iran, 55% of water needs are provided via groundwater resources. The annual amount of aquifer recharge by rainfall aquifer is 35 bm3. Annual water consumption is estimated to be 120 $\times 10^9$ m^3; about 66 $\times 10^9$ m^3 of it is provided by groundwater resources. Annual aquifer water consumption outstrips the annual recharge and has produced significant drops in water tables in 163 of 223 plains in the country (Zia 2004). The aquifer in Kashan plain is one of them with a critically low water level. It is crucial to develop a systematic plan for the management and protection of groundwater resources. The available groundwater levels must be measured and analyzed to preserve them. Modeling groundwater levels will help protect the environment, balance the groundwater system, control groundwater level fluctuations and protect against land subsidence as given by Affandi and Watanabe (2007). A number of models have been used to predict groundwater levels, including the experimental time series model and physical model (Izadi et al. 2007). When the dynamics of a hydrologic system change over time, these models may not be powerful enough to predict water parameters and have not been considered appropriate (Bierkens 1998).

Computer modeling of groundwater flow and transport has currently become a powerful tool for understanding and analyzing the hydrology of aquifers and various other aspects of Subsurface flow dynamics and various models are available for that purpose (Anderson and Woessner 1991, Kresic 1996, Sirhan and Koch 2013). These models usually look for a numerical solution of the fundamental differential equations that describe the physics of flow and transport in a porous subsurface media, after the latter has been put into a conceptual model-form, using geological and hydro-geological information on the aquifer system. In spite of, up-to-date, uncountable applications of numerical groundwater modeling to all kind of groundwater aquifer systems across the world, mostly with the goal to forecast the behavior of groundwater- flow or - levels in an aquifer under time-varying external stresses, such as, for example, increased pumping or changing aquifer recharge due to climate change, practical groundwater modeling can still be a formidable task (Sirhan and Koch 2013). This is less due to an inadequate mathematical translation of the deterministic physical flow system, but more due to an inadequate description of the latter itself, as geological, and hydro-geological data on the aquifer, as well as groundwater data, is often missing or fraught with errors (Sirhan and Koch 2013). To overcome some of these deficits of physically-based numerical models in poorly constrained real applications, alternative optimization methods have been suggested over the last two decades. The application of artificial intelligence (AI) for the analysis of data, especially long-series and large-scale data has become increasingly popular in different fields of engineering. Since the 1990s, artificial neural networks (ANNs), which are widely known as a branch of AI, have been gradually used to make hydrological predictions, which has been used widely over this period to describe the behavior of dynamic hydrologic systems in general (Smith and Eli 1995, Dibike et al. 1999, Govindaraju 2000, Maier and Dandy 2000, De Vos and Rientjes 2005, Wang et al. 2006, Chuanpongpanich et al. 2012), such as the responses of surface water runoff or stream flow to rainfall and groundwater levels fluctuation, i.e. ANN have been used as an alternative tool to traditional deterministic rainfall-runoff modeling (Sirhan and Koch 2013) and in forecasting groundwater levels fluctuation (Coulibaly et al. 2001, Affandi and Watanabe 2007, Affandi et al. 2007, Daliakopoulos et al. 2005, Lallahem et al. 2005, Nayak et al. 2004, Feng et al. 2008, Chitsazan et al. 2012, Mohanty et al. 2013). The results of studies performed by researchers such as (Ioannis et al. 2011, Sethi et al. 2010, Jothiprakash and Sakhare 2008, Bhattacharjya and Datta 2005) clearly showed that ANN can be used to predict water table level fluctuation and they used various algorithms and transport functions. In all of the studies that used ANN method in forecasting, the most suitable architecture of the ANN was determined by trial and error. So, the purpose of this study is to forecast the groundwater level fluctuation using ANN method in Kashan aquifer. For this purpose, to investigate the effects of hydrological, meteorological and human factors on the dynamic groundwater levels in the Kashan aquifer, we should forecast the results on the basis of Multiple Layer Perceptron (MLP) and Radial Basis Function (RBF) carried out by use of various education algorithm and transport function with trial and error method.

2. Materials and methods

The study area (longitude: 51°32'to 51°03'E, latitude: 33°27'to 34°13'N) is located in Kashan plain, Esfahan province, Iran (Fig.1). The Kashan plain has an area of 1570.23 km^2. The study area is located in a valley running from northwest to southeast. In this study, monthly groundwater level data were obtained from36 monitoring wells at different locations. Monitoring of groundwater level was carried out for a period of 20 years (1990 to 2010) (252 month). The selection of monitoring wells was based on their geological formations, land use and land cover. Based on Dumbarton's climate classification method, this area is a part of the arid and desert regions. The annual evaporation ranges from 2100 to 3000 mm. The average of annual humidity is about 42 percent. Maximum and minimum temperatures are +48°C and -5°C, respectively. Annual rainfall is varied spatially (75 mm in the east to 300 mm in the southwest mountains). The Kashan aquifer experiences an average annual loss of about 0.57 meter and a critical negative budget (about -32×10^6 m^3 annual discharge). The locations of study wells are shown in Figure (1). In this study the 80 percent of data were used for training, and the 5 and 15 percent of the remained data were used for validation and testing of the models respectively.

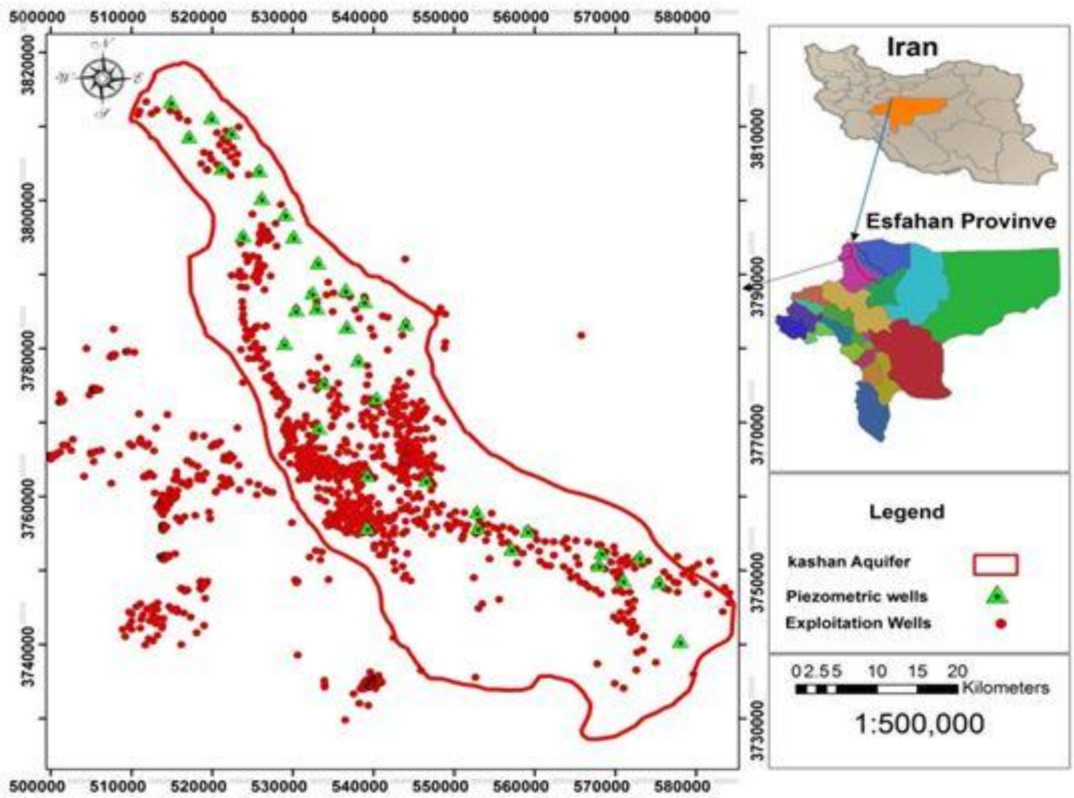

Fig. 1: Map of Piezometric and exploitation wells in the Kashan plain aquifer.

2.1. Data clustering

A statistical cluster analysis was conducted using all data sets of groundwater level time series. Cluster analysis is a statistical tool to classify the true groups of data according to their similarities to each other. Clustering methods (K-mean, hierarchical) commonly require variables that are similar in unit to be normalized at 0-1 (Bender et al. 2001) so that the clustering results are more appropriate (Alpaydin 2004). The hierarchy method was used based on Vard algorithm on the normalized groundwater level time series. These combined cluster density results were used to draw schematics of the approximate cluster size (Fig. 2). In these diagrams, the X axis is the number of piezometers minus one and the Y axis is a coefficient acquired using hierarchical method. Fig. 2 was used to find the point considered to be its land mark. The difference between the amount of the landmark over the X-axis and the number of piezometers is the approximate clustercount. This number is entered into the K-mean method to determine which piezometer is placed in which cluster (Zare Chahuki 2010).In this study, our data were grouped into 5 clusters.

Figure (3) indicates the time series of the variables. The primary y-axis is including X4, X5, X6, X7, X8, X9 and Y, and the secondary y-axis is including X1, X2 and X3 that were used for modeling the fluctuations of the groundwater level.

2.2. Artificial Neural Networks

ANNs are combinations of parallel exploitations of simple elements that were inspired by the neural system. ANN can be trained to do a practical function by regulating the weight relations between elements. Using actual data guides ANN output closer to the determined goal output to train the artificial neural network (Fig.4). The networks are then adjusted based on the comparison between the network and goal outputs until they are equal (Tassaloti 2003).

2.3. Models and network structures

In this study, Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) models were used to simulate water table fluctuations. The hyperbolic tangent transfer functions, linear hyperbolic tangent and sigmoid were used. Also used in group training were the Momentum algorithm, Levenberg-Marquardt, Quick Prop and Delta-Bar-Delta.

2.4. Selecting the best network configuration

The basis of teaching neural networks is trial and error, so the best network configuration is the one with a number of variations of hidden layers. Their neurons, activation functions, learning algorithms and replication of training are used to estimate the outcome parameter (Izadi et al. 2007). The basis of decision-making was to choose the best network in each implementation of mean square error (MSE) in Eq. (1), normalized mean square error (NMSE) in Eq. (2), root mean square error (RMSE) in Eq. (3), the correlation coefficient (R) and coefficient of determination (R^2) in Eq. (4) and adjusted R^2 in Eq. (5):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(qi - q\hat{i}\right)^2 \tag{1}$$

$$NMSE = \frac{MSE}{V} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(q_i - \hat{q}_i)^2} \tag{3}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(qi-\bar{q})\left(q\hat{i}-\bar{\hat{q}}\right)\right]^2}{\sum_{i=1}^{n}(qi-\bar{q})^2\sum_{i=1}^{n}\left(q\hat{i}-\bar{\hat{q}}\right)^2} \tag{4}$$

$$AdjustedR^2 = 1-\left(1-R^2\right)\frac{n-1}{n-p-1} \tag{5}$$

Where n is the data count, q_i is the number of observations, $q_{\hat{i}}$ is the estimated mean modeling output observation ($\bar{q}$) and calculation ($\bar{\hat{q}}$), V is the specific output variance, and P the number of neurons in the model entrance layer.

To simulate the quantitative status of the aquifer, the water depth for each cluster piezometer was used as an output model. Model entries and outputs were shown in table (1). About 85% of the data (213 month) were used to educate the network and 15% of the data (37 month) for the test. Afterward, each cluster was modeled using the MLP and RBF model for 48 architectures. After the best model was determined based on MSE, RMSE, NMSE, R, R2 and adjusted R2 statistical factors, model sensitivity to model entries was determined. The goal of analyzing model sensitivity was to create an effective model with fewer entries and simpler structures.

Table 1: Input and output parameters in groundwater level fluctuation modeling

Factors	Variable		Range of Values
Inputs	Rainfall (mm/day)	Fin station (X1)	0-129
		Bonrud station (X2)	0-173.5
		Mohammad abad station (X3)	0-105.5
	stream-flow discharge(lit/s)	Ghohrud station(X4)	25-741
		Bonrud tation (X5)	11-784
	Evaporation(mm/day)	Mohammad abad station (X6)	1.17-603.5
		Fin station (X7)	1.17-451.9
	Spring discharge(lit/s)	Cheshme Soleymanie (X8)	160-325
	Aquifer discharge(Mm^3)	Exploitation wells in study area(figure 1) (X9)	0.03-56
	Zayanderud discharge(lit/s)	The water source that transport from other basin (X10)	50-280
Outputs	Groundwater depth (m)	Piezometric wells in study area(figure 1) (Y)	13.5-87.28

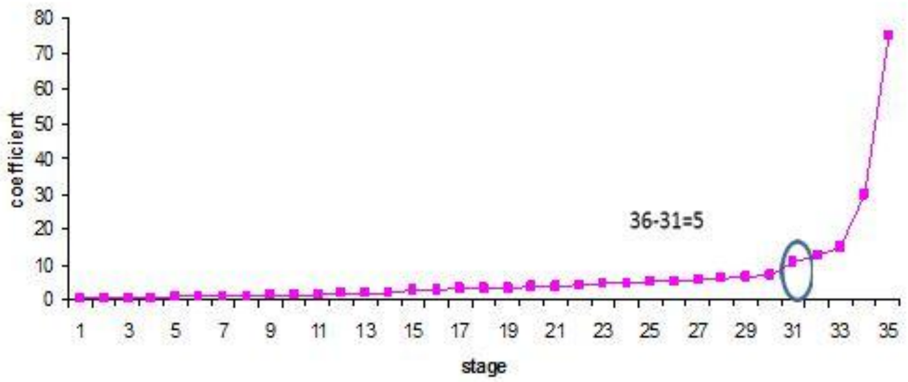

Fig. 2: Initial cluster count using hierarchy analysis.

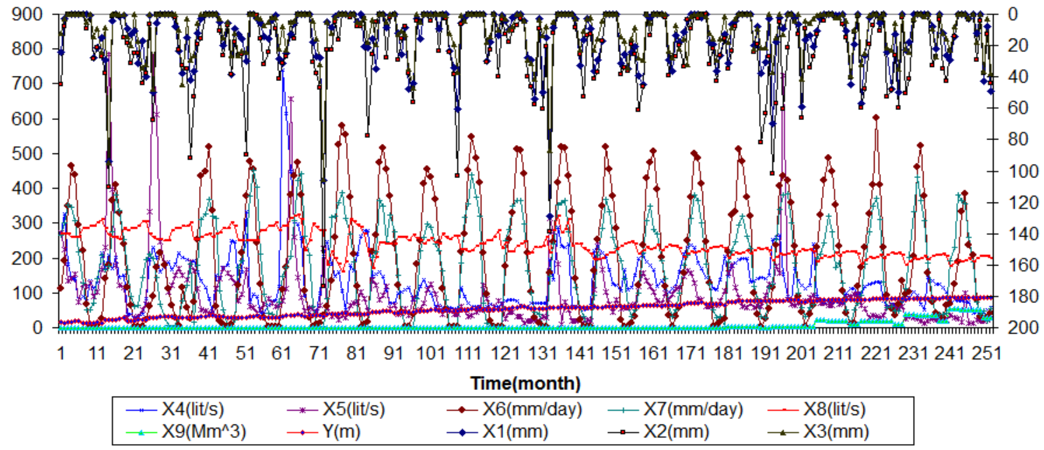

Fig .3: Time series of variable which used for modeling

3. Results and Discussion

Clustering 36 piezometers resulted in 5 clusters. To find the best model for each cluster, 48 architectures were analyzed using the MLP and RBF models. Optimum modeling for each cluster is shown in Table 2.

The results of the comparison of simulated depth versus water depth using MLP are shown in Fig. 5a,b,c,d,e. The result of sensitive analyze is show in Fig.6. The aim of the sensitive analyze is to find the most important parameters in modeling.

Clustering Piezometric wells allows access to relatively similar societies and samples from water depth fluctuations. Five cluster models allowed modeling of 5 cluster groups instead of 36 piezometers, decreasing the number of modeling needed, saving time and simplifying the analysis of the results.

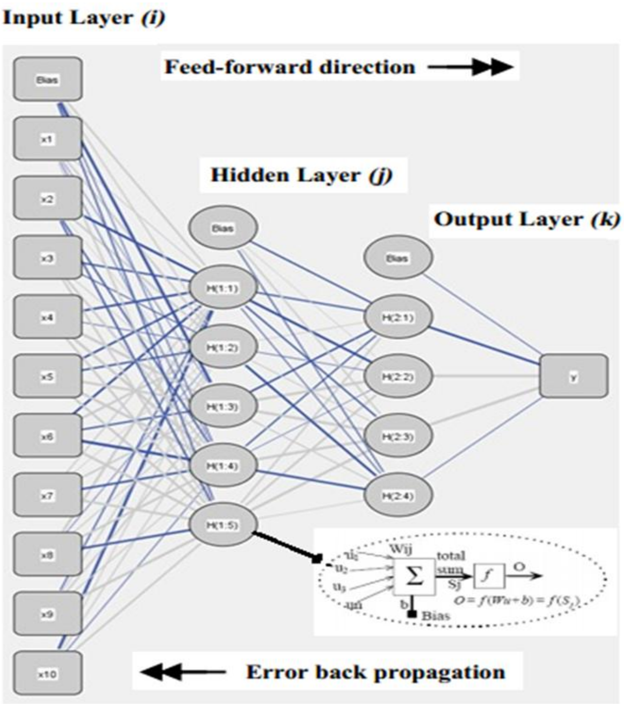

Fig. 4. Developed ANN Network for the present study

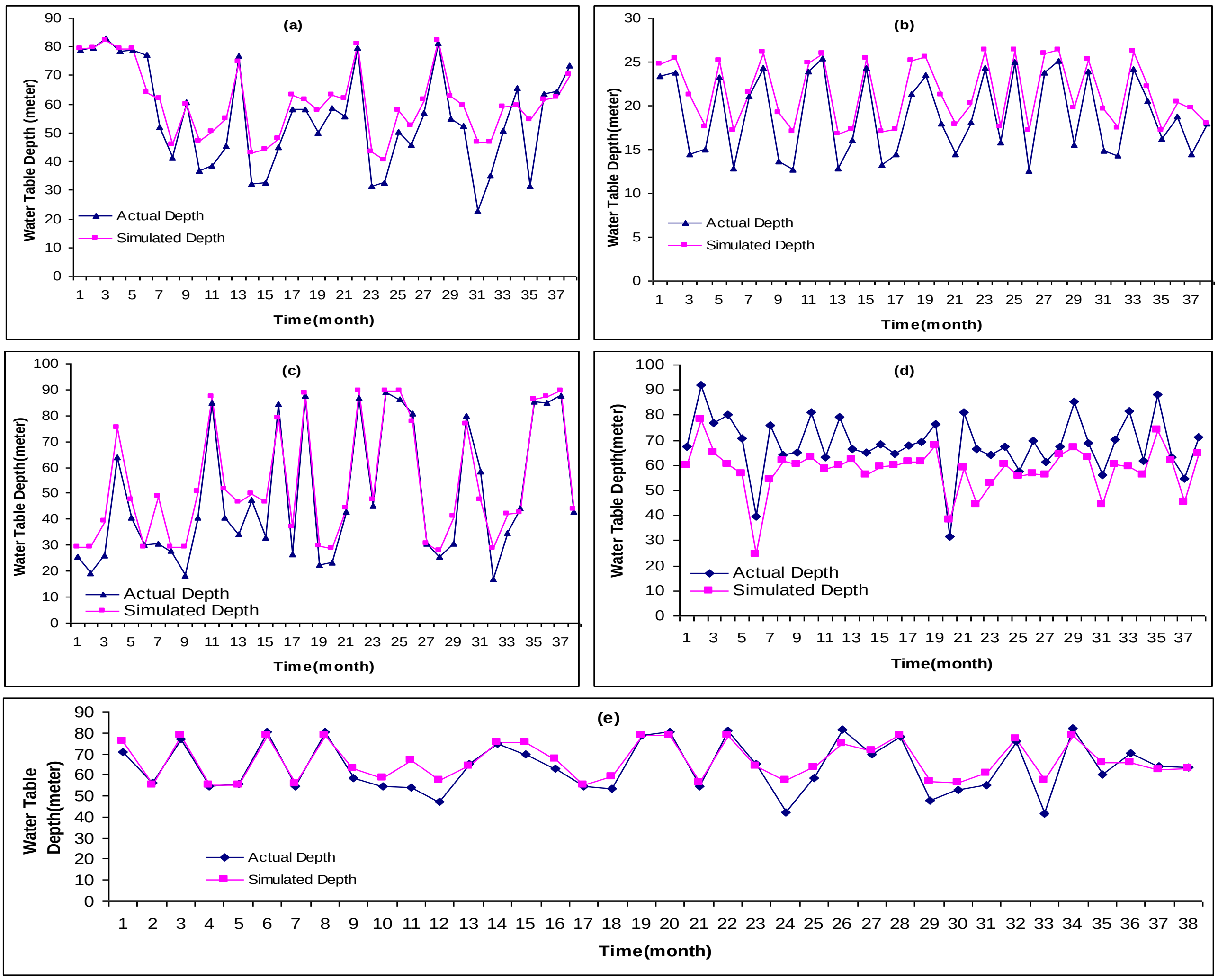

Fig. 5a, b, c, d, e : Simulated water table depth and actual depth using MLP model for cluster 1, 2, 3, 4 and 5.

The initial ANN-model trials were formatted using all ten input variables (neurons). From the 252 observed water levels, 80 percent of data were used for training, and the 5 and 15 percent of remind data were used for validation and testing of the models, respectively. Practically, the training of the network consists of a forward propagation of the inputs and a backward propagation of the error. In the forward procedure, the effect of an applied activity pattern at the input layer is propagated through the network layer by layer. During network training, the data are processed through the ANN, and the connection weights are adjusted adaptively, until a minimum acceptable error is achieved between the predicted and the observed output. Both, Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) ANN models were examined. Many different models with different numbers of hidden layers and different transport functions were tested. To that advantage, an intelligent problem solver (IPS) was developed to determine the model constraints including optimization time, network type and the number of hidden units, and paying attention to the relationships among all input variables. Astonishingly, the established MLP network with a hyperbolic tangent Axon in clusters 1, 2 and 3, a sigmoid in cluster 4 and linear hyperbolic tangent Axon transport function turned out to be better than a RBF- network.

Consequently, the latter ANN-option was not followed up further. In Fig. 5a,b,c,d,e the simulated water depth obtained for the MLP model in cluster 1 to 5 are plotted versus the observed water depth. In addition, the regression between the observed and simulated depth were shown the good performance for the MLP model. The Adjusted R^2 for cluster 1 to 5 (0.86, 0.88, 0.93, 0.55 and 0.79), the performance of this initial ANN model can be considered as a very good standard (Jothiprakash and Sakhare 2008, Affandi and Watanabe 2007, Yari 2008, Chitsazan et al. 2012, Mirarabi and Nakhae 2008, Daliakopoulos et al. 2005).

The results showed that the types of Education Algorithm and Transport Function are very important in modeling. So, in this study we use four Education Algorithms and Transport Functions, as we saw in Table 2, by change of data, Education Algorithm and Transport Function, the best model can be changed. In 60, 20 and 20 percent of models, Delta-Bar-Delta, Momentum and Levenberg-Marquardt were best Education Algorithms, respectively. In 60, 20 and 20 percent of models, hyperbolic tangent Axon, Sigmoid Axon and Linear hyperbolic tangent Axon were best Transport Function, respectively.

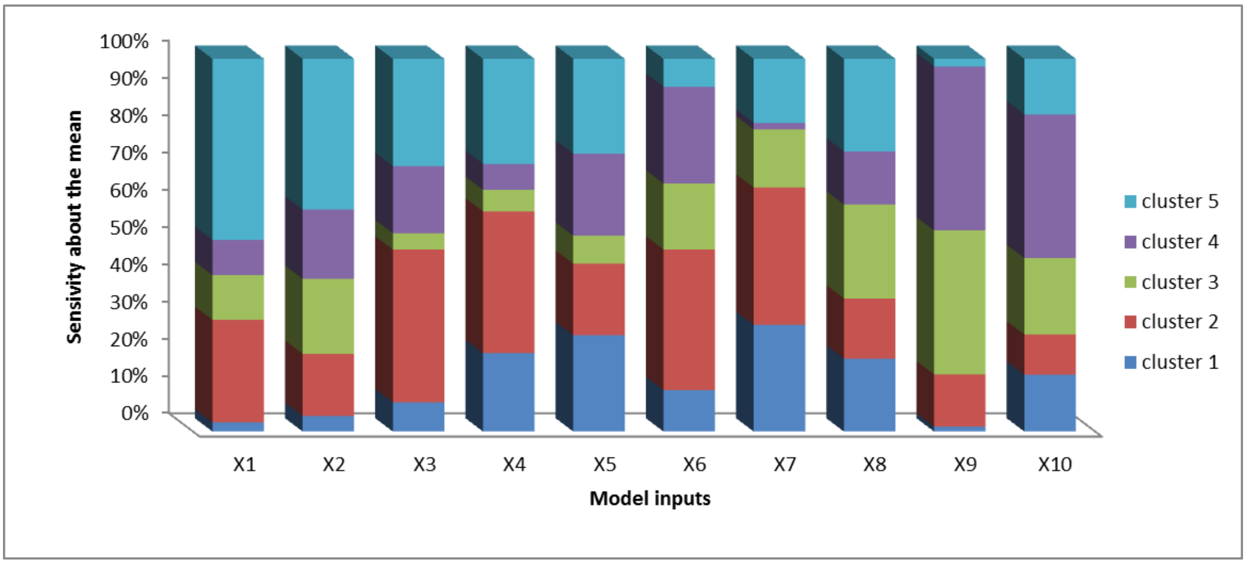

Fig: 6. Model output sensitivity for input parameters in all clusters based on MLP model

Table. 2: Properties of the optimum models in modeling using MLP and RBF model and five clusters

Cluster	Model	Number out of 48 models	Hidden layer count	Network configuration	Epoch	Education Algorithm	Transform function
First	MLP	23	2	5-4	307	Delta-Bar-	hyperbolic
	RBF	23	٢	5-4	1014	Delta	tangent Axon
Second	MLP	4	2	4-4	609	Delta-Bar-	hyperbolic
	RBF	23	2	5-4	818	Delta	tangent Axon
Third	MLP	13	2	4-3	413	Momentum	hyperbolic
	RBF	13	2	4-3	105		tangent Axon
Fourth	MLP	30	2	7-3	172	Levenberg-	
						Marquardt	Sigmoid Axon
	RBF	46	2	4-3	295	Delta-Bar-	
						Delta	
Fifth	MLP	40	2	4-3	77	Delta-Bar-	Linear
						Delta	hyperbolic
	RBF	44	2	5-4	473	Quick Prop	tangent Axon

MLP

Cluster	Train				Test					
	MSE	NMSE	R	R^2	MSE	NMSE	RMSE	R	R^2	Adjusted R^2
First	0.03	0.12	0.93	0.87	0.006	0.12	0.07	0.94	0.88	0.86
Second	0.01	0.11	0.94	0.89	0.001	0.10	0.03	0.95	0.90	0.88
Third	0.04	0.13	0.93	0.86	0.004	0.05	0.06	0.97	0.94	0.93
Fourth	0.0001	0.008	0.99	0.01	0.01	0.45	0.10	0.80	0.64	0.55
Fifth	0.04	0.15	0.91	0.82	0.005	0.15	0.07	0.91	0.82	0.79

RBF

Cluster	Train				Test					
	MSE	NMSE	R	R^2	MSE	NMSE	RMSE	R	R^2	Adjusted R^2
First	0.05	0.19	0.90	0.81	0.01	0.17	0.11	0.94	0.88	0.86
Second	0.02	0.18	0.90	0.81	0.002	0.13	0.04	0.93	0.87	0.84
Third	0.05	0.17	0.91	0.82	0.01	0.13	0.10	0.93	0.87	0.85
Fourth	0.05	0.67	0.57	0.32	0.01	0.65	0.12	0.62	0.38	0.30
Fifth	0.08	0.32	0.82	0.67	0.008	0.27	0.08	0.86	0.73	0.66

The sensitivity analysis from the different clusters based on the MLP model (Fig.6) shows that, Zayanderud transitional discharge, Soleimanie spring discharge, aquifer withdrawal discharge, Qohroud stream discharge, and rainfall from the Ghohrud watershed are the most important factors affecting on water depth fluctuations. Fin station and Bonrud rainfall had little effect on water depth fluctuations for area wells. Additionally, evaporation did not have a significant effect on the groundwater because the groundwater depth had dropped to below 5 m in the entire study area, which was too deep for evaporation to have much effect. There was no significant effect for evaporation in the simulation at the Muhammadabad and Fin stations. The results of this study and studies by Jothiprakash and Sakhre (2008), Ioanis et al (2011), Affandi and Watanabe (2007) and Chitsazan et al (2013) artificial neural network models showed high accuracy in simulating and predicting groundwater level fluctuations

4. Conclusion

The aim of this study was to assess of the feed forward neural network as a possible method for groundwater level forecasting in Kashan plain aquifer, Esfahan province, in the center of Iran. Rainfalls, rivers, transitional water resources from other basin and spring discharges (as aquifer recharge components), evaporation, and aquifer discharges (borehole wells) (as aquifer discharge components) were taken as inputs, and the groundwater levels of Kashan plain aquifer in five clusters (36 Piezometric well) were the outputs.

At first, the available data were divided into five clusters, according to hydrogeological, hydrological, meteorological and human factors on the dynamic groundwater levels characteristics of the Kashan plain. A back propagation (BP) neural network model with Momentum, Levenberg-Marquardt, Quick Prop and Delta-Bar-Delta algorithms have been studied in different hidden layers. The number of neurons on hidden layers also varied to optimize network. Often, the best results were obtained from the Delta-Bar-Delta and Levenberg-Marquardt algorithms. Based on statistical indices (R, R^2, Adjusted R^2, MSE, NMSE and RMSE), the best networks were determined for each hydrogeological cluster (Table.2). To verify the hydrogeological clusters and their neural networks, new observation data from September 1990 to March 2010 were introduced to the networks .Then, simulated groundwater levels were compared with actual groundwater of all clusters in the study area. The results were shown a good fit between real and calculated data by considering all clusters. Consequently, the study shows that training the artificial neural network with respect to effect of hydrological, meteorological and human factors on the dynamic groundwater levels gives good results.

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