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Estimation of groundwater level using a hybrid genetic algorithm-neural network

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ABSTRACT: In this paper, we present an application of evolved neural networks using a real coded genetic algorithm for simulations of monthly groundwater levels in a coastal aquifer located in the Shabestar Plain, Iran. After initializing the model with groundwater elevations observed at a given time, the developed hybrid genetic algorithm-back propagation (GA-BP) should be able to reproduce groundwater level variations using the external input variables, including rainfall, average discharge, temperature, evaporation and annual time series. To achieve this purpose, the hybrid GA-BP algorithm is first calibrated on a training dataset to perform monthly predictions of future groundwater levels using past observed groundwater levels and additional inputs. Simulations are then produced on another data set by iteratively feeding back the predicted groundwater levels, along with real external data. This modelling algorithm has been compared with the individual back propagation model (ANN-BP), which demonstrates the capability of the hybrid GA-BP model. The later provides better results in estimation of groundwater levels compared to the individual one. The study suggests that such a network can be used as a viable alternative to physical-based models in order to simulate the responses of the aquifer under plausible future scenarios, or to reconstruct long periods of missing observations provided past data for the influencing variables is available.

Key words: ANN, Coastal aquifer, GA-BP, Groundwater level, Simulation

INTRODUCTION

Estimation of groundwater level is very important in hydrogeology studies, aquifer management, and agriculture groundwater quality. In many cases, groundwater level fluctuations have resulted in irreparable damage to engineering structures. With considerable amounts of these fluctuations, appropriate decisions can be presented in terms of water quality, hydrogeology, and management purposes. Although, conceptual and physical based models are the main tools for understanding hydrological processes in a basin, they have application limitations because these models require large quantities of good quality data. Furthermore, they are also time-consuming processes for simulation. In this regard, it is of high importance to develop a fast and cost-effective method for aquifer simulation, continuously with an acceptable accuracy. In order to achieve this goal, many researchers have used intelligent systems. Amongst these researchers are Coulibaly et al. (2001), Lallahem and Mania (2003), Daliakopoulos et al. (2005), Lallahem et al. (2005), Dogan et al. (2008), Nourani et al. (2008), Yang et al. (2009), Sreekanth et al. (2009). These researchers used artificial neural networks for aquifer modelling in a variety of basins.

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A detailed review of ANNs applications can be found in Maier and Dandy (2000), Maier et al. (2010). They reviewed 43 papers dealing with the use of neural network models for the prediction of water resources variables. In recent years, Nourani et al. (2011) evaluates a hybrid of the Artificial Neural Network-Geostatic methodology for spatiotemporal prediction of groundwater levels in a coastal aquifer system. Jalalkamali and Jalalkamali (2011) employed a hybrid model of Artificial Neural Network and Genetic Algorithm (ANN-GA) for forecasting groundwater levels in an individual well. The hybrid ANN-GA model was designed to find an optimal number of neutrons for hidden layers. The consequences of their research admitted the superiority of the ANN-GA model in prediction of groundwater levels. Taormina et al. (2012) employed an artificial neural network for simulation of hourly groundwater levels in a coastal aquifer system. They confirmed that the developed feed-forward neural network (FNN) can accurately reproduce groundwater depths of the shallow aquifer for several months. Moreover, a method combined of the discrete wavelet transform method and different mother wavelets with ANN (WANN) was proposed by Nakhaei and Saberi Naser (2012) for the prediction of groundwater level fluctuations. Furthermore, a hybrid model of Neuro-Fuzzy Inference System with Wavelet (Wavelet-ANFIS) was proposed by Moosavi et al. (2013) for groundwater level forecasting in different prediction periods. These studies demonstrated that the wavelet transform can improve accuracy of groundwater level forecasting.

The studies' processes show that use of the more modern method is because of progression, and presentation of high accuracy in estimation of groundwater levels and high performance of computer speed and memory. The back-propagation algorithm (BP) is the most popular in the domain of neural networks, which is utilized in the most frequently mentioned studies for aquifers simulation. BP is the standard of the Gradient Descent algorithm. The Gradient Descent method, and therefore its algorithms, easily become stuck in local minimum and often needs a longer training time (Chau, 2007). In this study, the stochastic optimization method (GA) is utilized to train a feed forward neural network; therefore, numerical weights of neuron connections and biases represent the solution components of the optimization problem. In fact, a combination of genetic algorithm to adjust the neural network weights was proposed in several researches on artificial intelligence (Belew et al., 1991; Liang et al., 2000; Montana, 1995). GA is one type of stochastic algorithms that are capable of solving multi-dimensional complex problems, especially non-smooth, non-continuous, non-differentiable objective function to find the global optimum, to escape the local optima and acquire a global optima solution. This combination would be an efficient method of training neural networks because it takes advantage of the strengths of genetic algorithms and back propagation (the fast initial convergence of stochastic algorithms and the powerful local search of back propagation), and circumvents the weaknesses of the two methods (the weak fine-tuning capability of stochastic algorithms and a flat spot in back propagation). After performing the hybrid model and the ANN-BP model, this study presents results for estimation of groundwater levels in a coastal aquifer. Finally, a comparison of their results introduces the more optimum model for generation to other coastal aquifers.

Study area

The data used in this study are from the Shabestar Plain (Fig.1), which is located in the East-Azerbaijan province in the northwest of Iran. It is between 45° 26′ and 46° 2′ north latitude and 38° 3′ and 38° 23′ east longitude with a cold arid climate. The plain area is about 1,297 km^2 and its main river is the Daryanchai. The headwaters of the river are situated at a height of about 2,982m of the Misho Mountain, and it discharges to Urmia Lake. According to statistical results of data from the last 40 years, the average discharge of the Daryanchai River is 0.475 m^3/s. The mean daily temperature varies from -19°C in January up to 42°C in July with a yearly average of 11°C and an average annual rainfall of about 250 mm (Nourani and Ejlali, 2012).

As showed by Figure 1, the study area is a coastal aquifer system. There are about 25 plains around the Urmia Lake basin. The water levels of the lake have a tremendous environmental impact on the groundwater resources from these plains, especially in terms of salinity (Azizi and Abbasi, 2013). A significant population lives in the Urmia Lake basin, whose irrigation economics are strongly dependent on the existing surface, and groundwater resources in the area. Accordingly, the focus of the human population, indiscriminate use, and the recent droughts has reduced the lake's water level, and seasonal main river. So nowadays, groundwater is a major source of drinking and agricultural water supply.

Fig. 1. Study area in northwest Iran

This study has tried to evaluate the GA-BP and ANN-BP performance models and to provide a comparison of a more optimal model for the estimation of groundwater levels. For this purpose, the data were collected for nine years (from October 2000 to September 2009) with a one month time interval. The data utilized consist of observed groundwater level at 15 piezometers, average discharge of the Daryanchai River, annual time series, evaporation, rainfall, and temperature at the Sharafkhane Station. Table 1 shows the statistical analysis of the observed groundwater levels of piezometers. Furthermore, Figure 2 shows positions of the piezometers located within the Shabestar Plain. The chosen piezometers were selected based on uniform distribution in the plain, completeness of the data category, and far enough distance from the coastal line.

Table 1. Statistical analysis of observed groundwater in 15 piezometers

Piez. No.	X(UTM) (m)	Y(UTM) (m)	Mean (m)	Min (m)	Max (m)	Variance	Standard deviation (m)	Skewness Coefficient
P1	576150	4232500	1412.45	1408.31	1415.95	2.274615	1.508182	-0.047228
P2	579250	4235500	1363.58	1362.74	1365.67	0.407335	0.638228	0.778455
P3	561550	4225050	1334.10	1331.19	1357.68	7.269294	2.696162	6.299276
P4	572350	4225900	1329.07	1322.81	1336.86	25.60608	5.060245	0.168759
P5	577850	4228700	1311.56	1304.93	1318.91	12.27430	3.503471	0.880152
P6	577600	4222950	1298.84	1292.96	1300.16	0.632857	0.795523	-3.637452
P7	573100	4222550	1294.82	1292.31	1296.01	0.547359	0.739837	-0.491028
P8	554550	4220050	1283.90	1282.23	1286.22	0.871312	0.933441	0.152471
P9	546600	4223900	1279.37	1269.56	1282.44	3.421868	1.849829	-1.393301
P10	564200	4222000	1272.48	1265.55	1278.54	5.590902	2.364509	0.170974
P11	569900	4223500	1266.02	1259.51	1274.08	8.643071	2.939910	0.276150
P12	559350	4220800	1260.85	1257.32	1266.72	3.440292	1.854802	0.284084
P13	551800	4220150	1262.46	1256.44	1270.23	14.251235	3.775080	0.246874
P14	555200	4224100	1254.83	1250.83	1264.02	7.935692	2.817036	1.230776
P15	583700	4234500	1329.79	1328.99	1331.91	0.270965	0.520543	1.158132

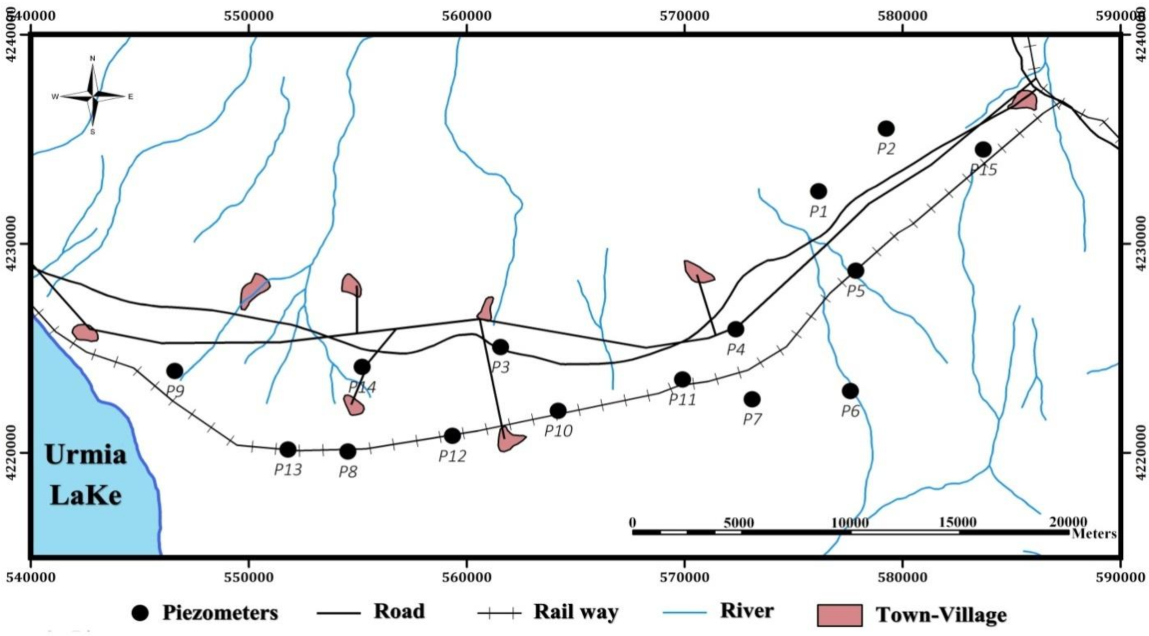

Fig. 2. Piezometer positions in Shabestar Plain

MARETIALS & METHODS

Artificial neural network (ANN)

Neural Networks basically comprise interconnected simulated neurons. In hydrological engineering applications to date, the most widely used network is the Feed-Forward Neural Network (FF-NN). This is largely due to its simplicity compared to other networks and its ability to learn the implicit governing relationship between the inputs and outputs if sufficient training data is supplied. FF-NN is a network structure in which the information or signals will propagate only in one direction.

The FF-NN typically consists of three layers, including input, hidden and output layers as depicted in Figure 3. It is possible to have more than one hidden layer but a single layer is sufficient to approximate any function to a desired degree of accuracy (Hornik et al., 1989). The number of neurons in the input and output layers are normally determined by the special problem. Furthermore, for most cases to date, the best way to determine the optimal number of neurons in the hidden layer is done by systemic trial and error. In fact, the inputs are fed through the input layer and, after being multiplied by synaptic weights, are delivered to the hidden layer. In the hidden neurons, the weighted sum of inputs is transformed by a nonlinear activation function, which is usually chosen as the logistic or the hyperbolic tangent. The same process takes place in each of the following hidden layers, until the outcomes reach the output neuron. Meanwhile, the linear activation function is most commonly applied to the output layer (Triana et al., 2010).

Back-propagation (BP) algorithms are the most popular training algorithms that are widely used due to their simplicity and the application for training FF-NN (Kulluk, 2013). In FF-BP networks, which are considered in this study, output error is reported back, and in this way, a more desirable output is acquired through updating the weighting coefficients matrix. This action is carried out until the error between the target data and output data derived from the weighting matrix is insignificant and consequently the value of the objective function is minimized (Fig.4). For further details on FF-NNs, the reader is referred to the bibliography (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000).

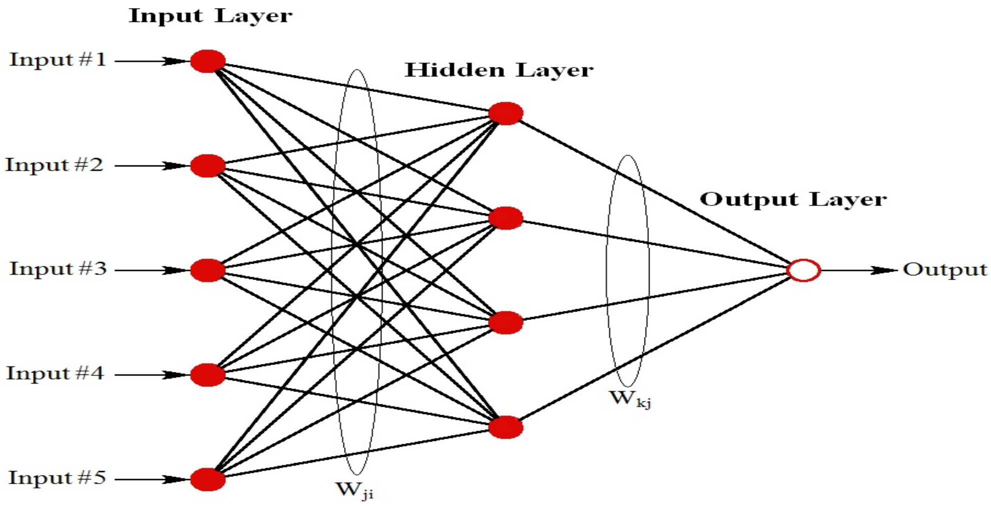

Fig. 3. Typical Feed-Forward Neural Networks

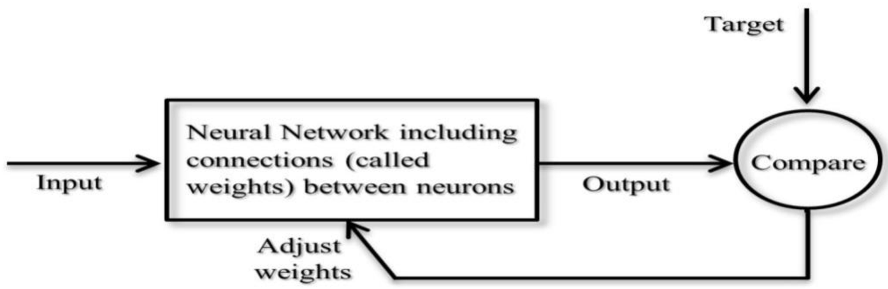

Fig. 4. Neural systems modify themselves in the training stage by adjusting weight values between neurons

Hybrid genetic algorithm-back propagation (hybrid GA-BP)

In order to avoid local optimum, the ANN learning process for the hybrid GA-BP model (Liang et al., 2000) consists of two stages: in the first stage, GA is employed to search for the optima or approximate optimal connection weights and biases for the network. Then in the second stage, the back-propagation training algorithm is used to adjust the final weights and biases (Fig.5).

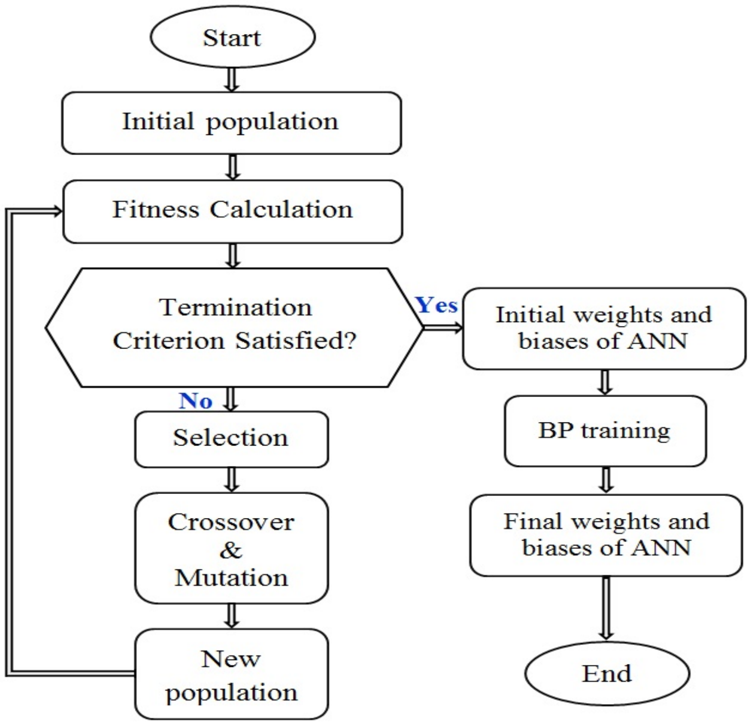

Fig. 5. GA-BP flow chart

GA is the most well-known evolutionary algorithm, which was introduced by John Holland and his colleague in the 1960s. The study of Jong and Goldberg et al. made significant progress in theoretical study as well as practical applications (Goldberg, 1989). This algorithm has an iterative progress, which begins the search with a random initial solution. In the hybrid GA-BP model, the ANN weights and biases are initialized as genes of chromosomes, and then for searching for the global optimum, three operators (*selection*, *crossover*, and *mutation*) are used to generate the next population. GA is stopped when the stopping criteria (e.g., number of generation, stall generation, time limit and so on) is met. After that, this procedure is completed by applying a BP training algorithm on GA established initial connection weights and biases (Fig.5).

RESULTS & DISCUSSION

In this study, the hybrid GA-BP model is designed in comparison with the ANN-BP model for estimation of groundwater levels. For this purpose, the weights adjustment is done through minimizing the objective function, which is normally defined as a root mean squared error (RMSE), which calculates according to Equation 1.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{1}{N} (WL_{observed} - WL_{predicted})} \qquad (1)$$

In this equation, RMSE is the root mean squared error, N is the number of training samples, $WL_{observed}$ is the amount of observed groundwater levels for each piezometer, and $WL_{predicted}$ is the predicted groundwater level using the GA-BP or ANN-BP model.

As has been explained, the utilized dataset was acquired for October 2000 to September 2009 including Rainfall (mm/month), average discharge of the Daryanchai River (m^3/s), temperature ($^{\circ}C$), evaporation (mm/month), and annual time series (year), which was defined as the external inputs for determining groundwater fluctuations from 15 piezometers. According to recent researches (Coulibaly et al., 2001a; Lallahem et al., 2005; Nourani et al., 2008) effective factors in the fluctuation of groundwater levels include temperature, rainfall and average discharge of the basin. However, typical hydrology and hydrogeology of every basin are different. In the coastal aquifer of the Shabestar Plain, groundwater levels decreased in all piezometers. Undoubtedly, evaporation also has an important role in these decreases. So, in this case study the evaporation data were added to the input layer. Furthermore, in another case study, the evaporation factor is used for the estimation of groundwater levels in another coastal aquifer located in Italy (Taormina et al., 2012). These four input data (temperature, rainfall, average discharge and evaporation) reflect monthly fluctuations in the groundwater level since piezometer groundwater levels decrease with a constant gradient annually, annual time series are also included in the present study. Rainfall values ranged from 3 to 110.2 mm/month (average 20.39), average discharge value from 0.03 to 2.658 m^3/s (average 0.41), temperature value from -6.7 to 27°C (average 13.41) and evaporation value from 0 to 265.9 mm/month (average 87.39).

For better assessment of the results, all input and output data were normalized using the method introduced by Larose in data mining and statistical analysis (Larose, 2005). Normalization is performed in the typical range of 0 (L) and 1 (H) by using the maximum and minimum values according to Equations 2-4.

$$X^* = mX_i + b \tag{2}$$

$$m = \frac{H - L}{Max(X) - Min(X)} \tag{3}$$

$$b = \frac{Max(X)L + Min(X)H}{Max(X) - Min(X)} \tag{4}$$

where, X^* are the normalized and X_i are main variables.

Table 2 represents the parameters that were used in construction of the GA-BP model. Structure of the ANN-BP model designed (5:7:1) for both models consists of three layers, including the input layer, hidden layer and output layer, as shown in Figure 6. Architecture of the feed forward BP neural network consists of five input variables, seven hidden neurons with hyperbolic tangent function and one output variable with a linear activation function, transform the sum of all the weighted inputs into an output signal. By using a trial and error method it was realized that a structure with seven neurons in the hidden layer (5:7:1structure) gives the best results.

Table 2. Parameters used in the construction of the GA-BP model

GA-BP Properties	Properties
Initial population	40
Maximum number of generations	50
Number of elite children	4
Fraction of crossover children	0.75
Number of mutation children	9
Number of neurons in hidden layer	7
Transfer function from layer 1 to 2	TANSIG
Transfer function from layer 2 to 3	PURELIN

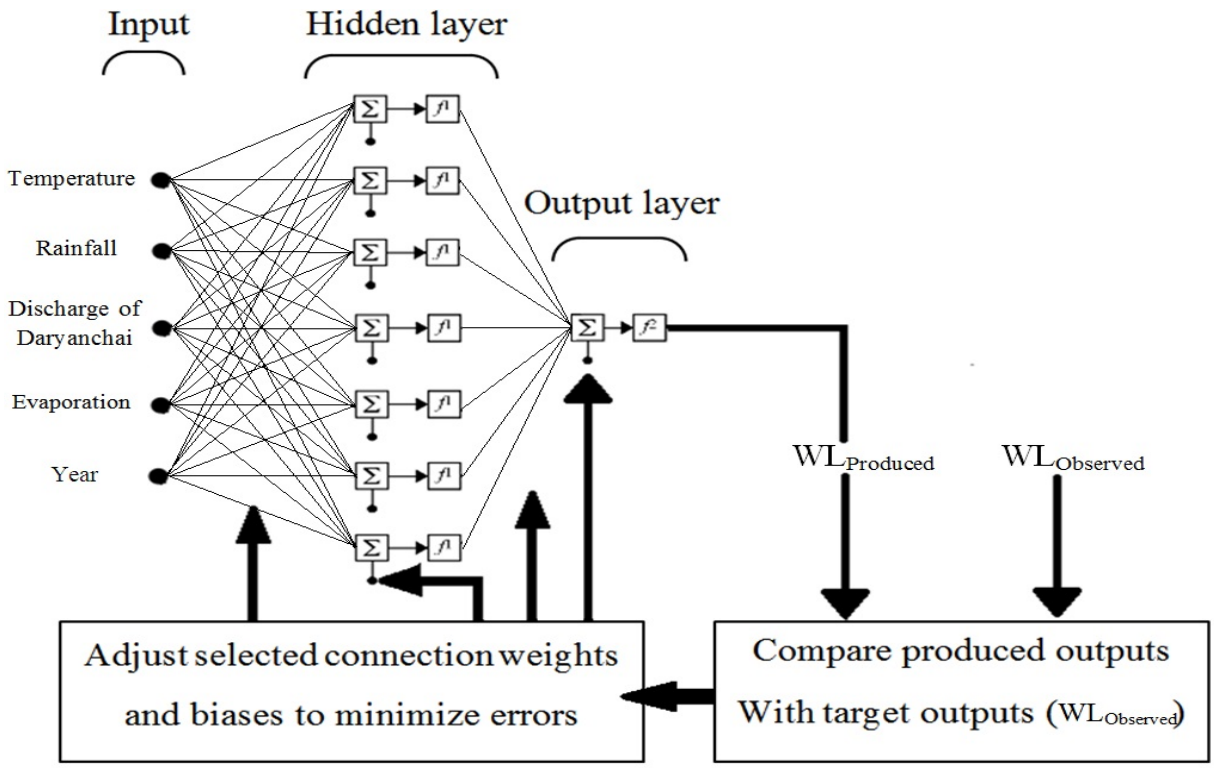

Fig. 6. Typical Architecture of feed forward BP neural network with seven neurons in the hidden layer (Hosseini, 2013); by comparing produced groundwater level ($WL_{Produced}$) and observed groundwater level ($WL_{Observed}$) during the training phase, errors propagate backward to the connections in the previous layers.

To make an appropriate comparison between the different intelligent optimization methods the same set of input/output data and training, testing and validation data were used. Meanwhile, the same parameter settings for the individual and hybrid models were used. The total dataset includes 84 training data for each piezometer (October 2000 to September 2007), 12 testing data (October 2007 to September 2008) and 12 validation data (October 2008 to September 2009) for evaluating its accuracy. RMSE and correlation coefficient (R^2) between the observed and estimated data were calculated as criteria to evaluate their accuracy.

All results of the training and test stage for each model (GA-BP and ANN-BP models) are shown in Table 3. It can be observed that the performance of GA-BP model is much better than that of the ANN-BP model in training, testing and validation data. According to Table 3, the GA-BP model has the best performance in the training step, providing the best results for test data. Average RMSE and R^2 between observed and estimated data using the GA-BP model in training data from 15 piezometers are 0.026 and 0.98, respectively. These amounts for test data are calculated 0.03 and 0.873, and 0.049 and 0.843, respectively, for the validation set. Furthermore, average RMSE and average R^2 between observed and predicted groundwater level using the ANN-BP model are 0.036 and 0.965, respectively, in training data, and 0.042 and 0.778, respectively, in test data, as well as 0.068 and 0.768 in the validation data.

The results of the prediction at 3 piezometers (P4, P8 and P13) that were illustrated for a clearer comparison between the performances of the GA-BP and ANN-BP models are presented in Figure 7 and Figure 8. These image plots show a graphical comparison between observed groundwater level and estimated data by using two intelligent models for testing data. The results clearly show that the GA-BP model is more successful among the individual models designed (ANN-BP) in this study. This model is faster than GA stochastic models. So, the GA-BP model can be of high prominence in the estimation of groundwater levels.

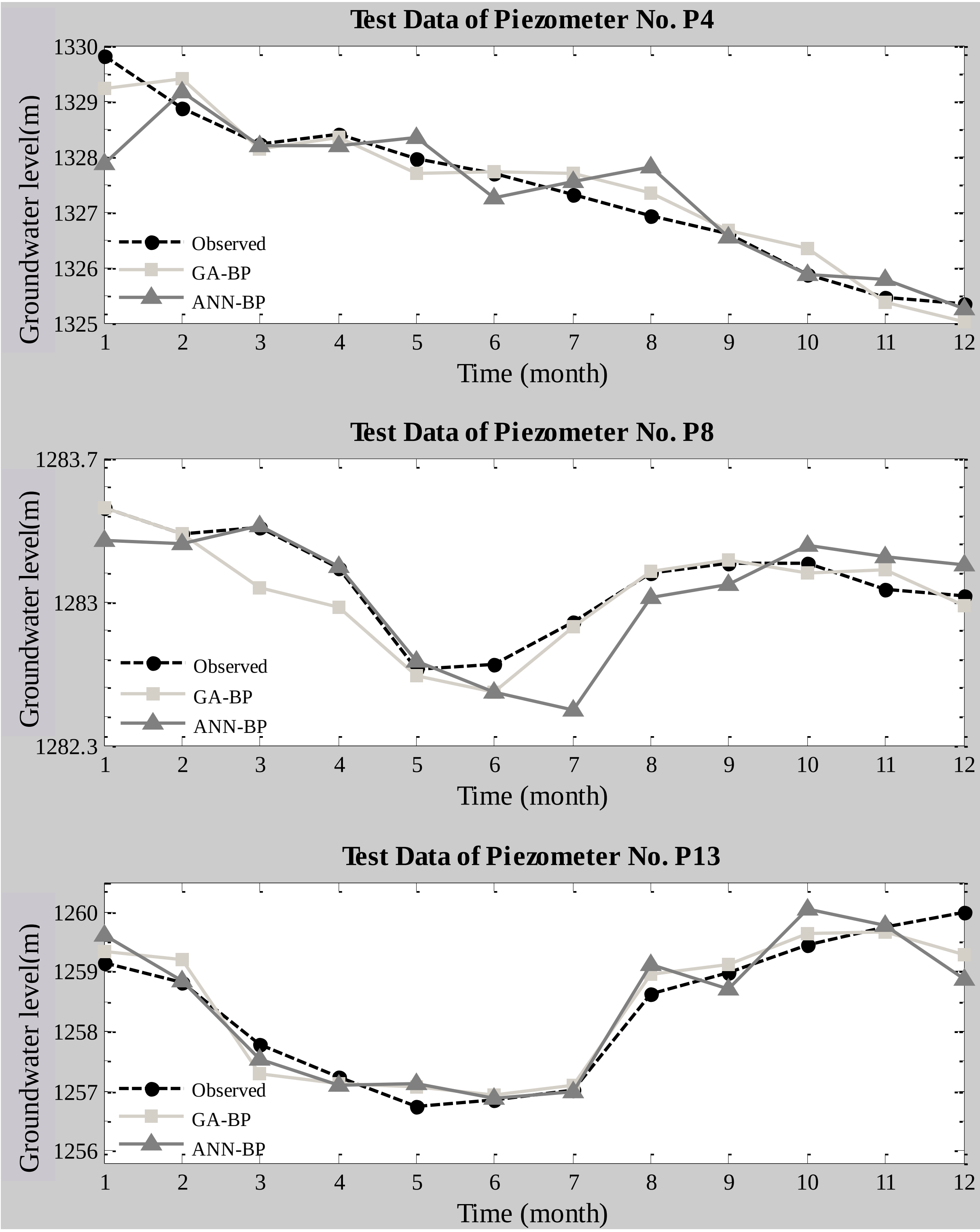

Fig. 7. Graphical comparison of estimated versus observed groundwater level at selected piezometers using GA-BP and ANN-BP in test stage

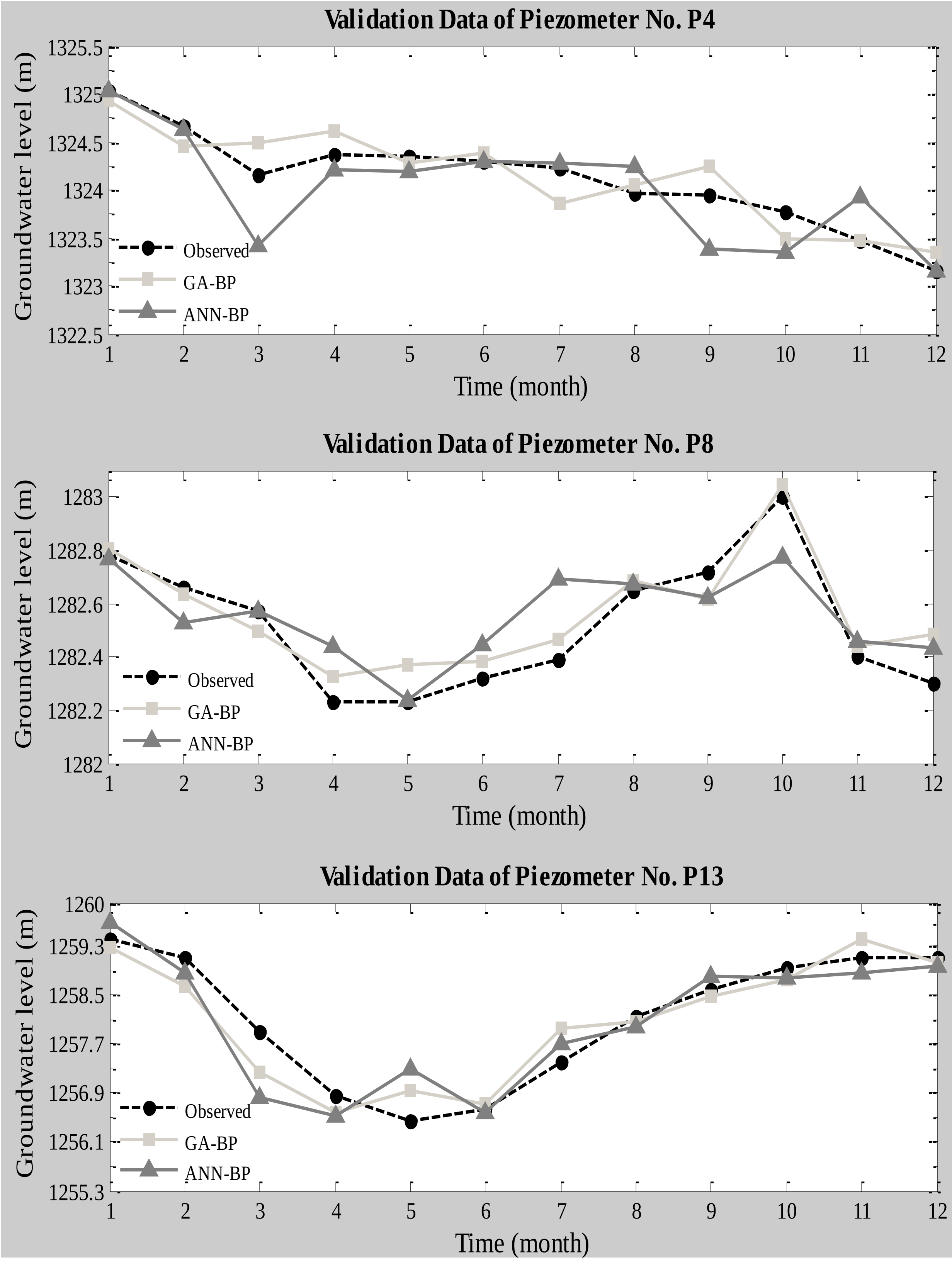

Fig. 8. Graphical comparison of estimated versus observed groundwater levels at selected piezometers using the GA-BP and ANN-BP models in the validation stage

Table 3. The results of models for estimation of normal groundwater levels

Piez. No.	GA-BP						ANN-BP					
	Training		Test		Validation		Training		Test		Validation	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
P1	0.037	0.974	0.039	0.917	0.043	0.848	0.041	0.971	0.047	0.821	0.046	0.805
P2	0.026	0.986	0.032	0.905	0.028	0.786	0.032	0.974	0.041	0.757	0.051	0.758
P3	0.011	0.987	0.017	0.685	0.011	0.532	0.011	0.985	0.02	0.452	0.013	0.479
P4	0.015	0.994	0.024	0.967	0.015	0.904	0.039	0.972	0.047	0.881	0.024	0.828
P5	0.021	0.991	0.021	0.751	0.023	0.976	0.027	0.976	0.038	0.586	0.029	0.952
P6	0.023	0.973	0.026	0.856	0.031	0.833	0.038	0.925	0.033	0.728	0.042	0.682
P7	0.036	0.976	0.039	0.896	0.053	0.873	0.053	0.959	0.079	0.792	0.071	0.619
P8	0.025	0.974	0.028	0.919	0.027	0.907	0.033	0.965	0.041	0.849	0.036	0.815
P9	0.009	0.992	0.011	0.911	0.013	0.871	0.015	0.981	0.015	0.845	0.017	0.883
P10	0.025	0.987	0.032	0.825	0.027	0.86	0.031	0.956	0.04	0.771	0.47	0.648
P11	0.035	0.976	0.035	0.901	0.037	0.877	0.036	0.971	0.038	0.866	0.039	0.812
P12	0.041	0.965	0.045	0.947	0.049	0.932	0.062	0.942	0.063	0.922	0.063	0.927
P13	0.022	0.996	0.024	0.962	0.025	0.941	0.031	0.989	0.032	0.92	0.031	0.906
P14	0.041	0.963	0.046	0.91	0.051	0.835	0.053	0.956	0.06	0.831	0.055	0.816
P15	0.024	0.969	0.036	0.751	0.031	0.675	0.033	0.953	0.037	0.653	0.038	0.597

CONCLUSION

In this study, the GA-BP and ANN-BP models are designed to estimate groundwater levels in the Shabestar Plain. The nine years of monthly average data including rainfall, temperature, river discharge, annual time series and evaporation criteria, were used as inputs and groundwater level data were considered as output of the models. Results of this study showed that the GA-BP model has better performance than each model individually (GA and ANN-BP models). Results of the simulation with the GA-BP and the ANN-BP models for all piezometers show that average RMSE for testing data are 0.03 and 0.042, respectively. Data for the validation stage are 0.049 and 0.068, respectively. Furthermore, average R^2 of the testing and validation set was 0.873 and 0.843 for the GA-BP model and 0.778 and 0.768 for the ANN-BP model, respectively. The findings of this research demonstrate that employing a genetic algorithm to initialize neural network connection weights in complex space avoids the risk of becoming stuck in local minima. Therefore, in water resources management projects, it can prevent high costs and time wasting for drilling more piezometers. It is expected that the GA-BP model is capable of identifying groundwater levels in other coastal aquifers.

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