International Journal of Soft Computing and Engineering (IJSCE)
ISSN: 2231-2307, Volume-2 Issue-1, March 2012

Classification of Groundwater Level Data Using SOM to Develop ANN-Based Forecasting Model

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***Abstract*— Prediction of groundwater level in a watershed plays a crucial role in management of groundwater resources, especially in a semi-arid area where there is immense need to groundwater resources in order to prepare the requirement water for agriculture, municipal and industrial affairs.**

The aim of this study is to present a mathematical based model to estimate the groundwater level (GWL) in Ardabil located at northwest of Iran, with association of some hydrological data (e.g., rainfall, discharge, etc.). In this way identifying various zones with similar groundwater level can be a promising idea which leads to appropriate overview on water table of the study area as well as efficient modeling.

For this purpose, the Self Organizing Map (SOM) was used to cluster the homogenous monitoring piezometers in the plain by utilizing GWL and Universal Transverse Mercator (UTM) data. The sensitivity analysis was performed over normalized and non-normalized data of GWL and UTM in order to investigate their effects on clustering. Conventional K-Means method was applied to verify the results of SOM method. The central piezometer of each cluster was selected as a representative by means of statistical technique. Afterwards the three layer feed forward Artificial Neural Network (ANN) model was utilized to calibrate a model via historical groundwater level records from the representative wells and relevant hydro-meteorological data. The last step was performed by simulating water table level of the representative piezometer from each zone of the plain via proposed model, to compare the computed and observed data. The results reveal the suitability of SOM clustering method with normalized data of GWL and also identify the specific piezometers that the GWL of them can represent the GWL in a particular region. Thus, adequate measures should be devoted on preserving such important monitoring piezometers and reliable data can be obtained from them in order to generalize the GWL data to that specific region. The modeling results can be utilized to frame the corresponding strategies to reduce the monitoring cost and to enhance the cost-effective benefits. The proposed methodology can be referred as a management plan for groundwater resources.

Index Terms*— Ardabil Plain, Artificial Neural Network, Clustering, Groundwater level, Self Organizing Map.

I. INTRODUCTION

In different parts of the world, groundwater is a significant water resource for domestic, industrial, and agricultural activities. For an effective management of groundwater, it is important to predict groundwater level fluctuations. Accurate and reliable model in forecasting groundwater level can ensure the sustainable use in watershed aquifers for urban and rural water supply. In an applicatory classification Adamowski and Chan categorized the effects and applications of precise groundwater level prediction as below: (i) development of efficient strategies to avoid or reduce adverse effects such as loss of pumpage in residential water supply wells, land surface subsidence, and aquifer compaction; (ii) elaborate informative data in subject of the dynamics and underlying factors that affect groundwater levels; and (iii) management of water demands which are obviated by groundwater consumption such as urban, agricultural and industrial requirements [1].

Groundwater systems possess features such as complexity, nonlinearity, being multi-scale and random, all governed by natural and/or anthropogenic factors, which complicate the dynamic predictions. Therefore, many hydrological models have been developed to simulate this complex process [2]. Models based on their involvement of physical characteristics generally fall into three main categories: black box models, conceptual models, and physical-based models [3]. The conceptual and physical-based models are the main tools for predicting hydrological variables and understanding the physical processes that are taking place in a system. However, they have a number of practical limitations, including the need for large amounts of hydro-geological data sophisticated programs for calibration using rigorous optimization techniques, and a detailed understanding of the underlying physical process [2].Due to the recognized limitations of these models, data-based methods such as artificial neural network (ANN) models (i.e., a black box models) has been widely used for forecasting in many areas of science and engineering. There are vast surge of reports on application of ANN in groundwater related field such as groundwater level-prediction or contamination.

Lallahem et al. used artificial neural network (ANN) methodology for estimating the groundwater level in some piezometers implanted in unconfined chalky aquifer of Northern France [4]. The reasonably good ANN-based simulations revealed the merit of using ANNs and specifically Multi Layer Perceptron (MLP) models. Daliakopoulos et al. forecasted groundwater level by using ANNs [5].

Revised Manuscript Received on March 2012.

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They identified an optimal ANN architecture trained with a standard feed-forward neural network trained with the Levenberg–Marquardt algorithm that could simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 18 months ahead. Nourani et al. evaluates the feasibility of ANN methodology in estimating the groundwater levels at some piezometers placed in an aquifer in north-western Iran [6]. They approved that ANNs based on the nonlinear intrinsic approach, provide accurate predictions. In another study, Yang et al. employed the Integrated Time Series (ITS) and Back-Propagation Artificial Neural Network (BPANN) models to forecast groundwater levels [7]. The results revealed the suitability of BPANN model in forecasting the groundwater level. Nourani et al. studied the spatiotemporal variations of the water level for the management of groundwater in the coastal areas [2]. They employed a hybrid, artificial neural network-geostatistics methodology for spatiotemporal prediction of groundwater levels. Amir and Navid Jalalkamali employed a hybrid model of artificial neural network (ANN) and genetic algorithm (GA) in forecasting groundwater level in an individual well [8]. The consequences of their research admitted the superiority of ANN-GA model in prediction of groundwater level. Moreover, a method coupled of discrete wavelet transforms (WA) and ANN was proposed by Adamowski and Chan in to predict groundwater level in Canada [1]. The results of their study indicated the potential of WA-ANN models in forecasting groundwater level.

Cluster analysis is a statistical method of partitioning samples into homogeneous classes to produce an operational overview on data sets. The importance of cluster analysis techniques is evident in classifying multivariate data into subgroups. Clustering techniques identify structure in an unlabeled data set by objectively arranging data into homogeneous groups, where the within-group-object dissimilarity is minimized and the between-group-object dissimilarity is maximized. There are divers kinds of mathematical based methods in order to cluster data. The requirement to clustering techniques in hydrological and environmental filed especially groundwater related researches have been raised in recent decade.

For instance, Kim et al. enjoyed the cluster analysis results in determination of hydro-geochemical characteristics of shallow groundwater in coastal area [9]. Multivariate statistical techniques, such as cluster analysis and principal component analysis were performed on 22 well representative groundwater samples. The collected samples were analyzed for water quality variables [10].

The sustainable management of groundwater resources in a watershed is one of the important issues of hydrological and environmental studies. Accurate assessment of groundwater level is an authoritative appliance in attaining the adequate management policies. Implanted piezometers all over the watershed can prepare informative data about the fluctuations of ground water level in a region. Thus the identification of dominant piezometers in a watershed that exhibit reliable data plays a crucial role in sufficient groundwater management. Application of clustering techniques on available piezometers interspersed spatially over the watershed can be an appropriate method to capture the adequate information of homogeneous piezometers. Indeed, by performing clustering techniques a spatial pre-processing approach is imposed on several pizometery data. The precise investigation on pizeometry data classification reveals prominent piezometers.

Among the various clustering methods, the conventional clustering methods (e.g., K-Mean) require the number of clusters be specified in advance, and their results are relevant to linear characteristics [11].The SOM operates as an effective tool to convert complex, nonlinear, statistical relationship between high-dimensional data items into simple, geometric relationship on a low-dimensional display so as to allow the number of clusters to be determined by inspection [12]. The SOM based classification is attractive, due to its topology preserving properties for solving various problems that traditionally have been the domain of conventional statistical and operational research techniques. SOMs have been successfully accepted widely in science and engineering problems; not only are their results unbiased, but they can also be visualized.

Peeters et al. Compared the performance of the GEO3DSOM (a variant of the SOM-algorithm which is capable of explicitly incorporating three-dimensional spatial knowledge into the algorithm) and standard SOM in analyzing an artificial data set and a hydro-chemical data set [13]. Both techniques succeed very well in providing more insight in the groundwater quality data set, visualizing the relationships between variables, highlighting the main differences between groups of samples and pointing out anomalous wells and well screens. The GEO3DSOM however has the advantage to provide an increased resolution while still maintaining a good generalization of the data set. Chen et al. used the combination of the back-propagation network (BPN) and the self-organizing map (SOM) for forecasting the groundwater level data in southern Taiwan [14]. According to their results, the multisite SOM-BPN model has the highest accuracy. Kalteh et al. prepared a review paper to discuss the analysis, modeling and application of SOM approach in water resources [15], another review of SOM applications in meteorology and oceanography is reported by Liu and Weisberg as well [16].

The objective of this study is to predict groundwater level pattern of the prominent pizeometers at time scale of one month ahead in Ardabil Plain via SOM-ANN model.

The rest of this paper is organized as follows: In the next two sections, the concepts of ANN, and SOM are briefly reviewed, respectively. Section 4 describes the study area and efficiency criteria. Section 5 presents and discusses the results obtained by implication of the proposed methodology. The final section of the paper is concluding remarks.

II. ARTIFICIAL NEURAL NETWORK (ANN)

ANN is widely applied in hydrology and water resource studies as a forecasting tool. In ANN, feed–forward back–propagation (BP) network models are common to engineers. It has proved that BP network model with three–layer is satisfied for the forecasting and simulating in any engineering problem [17]-[18].

As shown in Fig.1, three–layered feed forward neural networks (FFNNs), which have been usually used in forecasting hydrologic time series, provide a general framework for representing nonlinear functional mapping between a set of input and output variables. In the Fig.1, *i*, *j* and *k* denote input layer, hidden layer and output layer neurons, respectively and *w* is the applied weight by the neuron. The term "feed–forward" means that a neuron connection only exists from a neuron in the input layer to other neurons in the hidden layer or from a neuron in the hidden layer to neurons in the output layer and the neurons within a layer are not interconnected to each other. The explicit expression for an output value of a three-layered FFNN is given by[19]:

$$\hat{y}_k = f_{\circ}\left[\sum_{j=1}^{M_N} w_{kj} \cdot f_h\left(\sum_{i=1}^{N_N} w_{ji} x_i + w_{jo}\right) + w_{ko}\right] \qquad (1)$$

where w_{ji} is a weight in the hidden layer connecting the *i*th neuron in the input layer and the *j*th neuron in the hidden layer, w_{jo} is the bias for the *j*th hidden neuron, f_h is the activation function of the hidden neuron, w_{kj} is a weight in the output layer connecting the *j*th neuron in the hidden layer and the *k*th neuron in the output layer, w_{ko} is the bias for the *k*th output neuron, f_o is the activation function for the output neuron, x_i is *i*th input variable for input layer and $\hat{y}_k$, y are computed and observed output variables, respectively. N_N and M_N are the number of the neurons in the input and hidden layers, respectively. The weights are different in the hidden and output layers, and their values can be changed during the process of the network training.

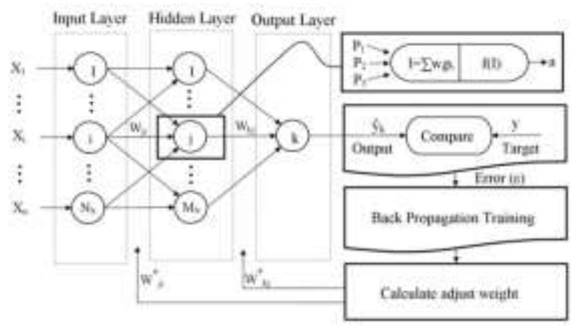

Fig. 1. A three-layered feed-forward neural network with BP training algorithm.

III. SELF ORGANIZING MAP

The self-organizing map (SOM) is an effective software tool for the visualization of high-dimensional data. It implements an orderly mapping of a high-dimensional distribution onto a regular low-dimensional grid. Thereby it is able to convert complex, nonlinear statistical relationships between high-dimensional data items into simple geometric relationships on a low-dimensional display while preserving the topology structure of the data [20]. The way SOMs go about reducing dimensions is by producing a map of usually 1 or 2 dimensions which plot the similarities of the data by grouping similar data items together. Thus SOMs accomplish two things; they reduce dimensions and display similarities. The SOM network generally consists of two layers, an input layer and a Kohonen layer. The input layer is fully connected to the Kohonen layer, which in most common applications is two-dimensional. A two-level SOM neural network is a promising approach to catch a preliminary overview on intricate data set. It augments the conventional SOM network with additional one-dimensional Kohonen layer in which each neuron is connected to neurons in the previous Kohonen layer. The schematic view of the two-level SOM network is shown in Fig.2.

The SOM is trained iteratively: Initially the weights are randomly assigned. When the n-dimensional input vector ***x*** is sent through the network, the distance between the weight ***w*** neurons of SOM and the inputs is computed. The most common criterion to compute the distance is Euclidean distance [20]:

$$\| x - w \| = \sqrt{\sum_{i=1}^{n} (x_i - w_i)^2} \qquad (2)$$

The weight with the closest match to the presented input pattern is called winner neuron or Best Matching Unit (BMU).The BMU and its neighboring neurons are allowed to learn by changing the weights at each training iteration *t*, in a manner to further reduce the distance between the weights and the input vector [20]:

$$w(t+1) = w(t) + \alpha(t) h_{\mathrm{lm}} (x - w(t)) \qquad (3)$$

Where α is the learning rate, ranging in [0 1], *l* and *m* are the positions of the winning neuron and its neighboring output nodes and h_{lm} is the neighborhood function. The most commonly used neighborhood function is the Gaussian [20]:

$$h_{\mathrm{lm}} = \exp\left(-\frac{\| l - m^2 \|}{2\sigma(t)^2}\right) \qquad (4)$$

where h_{lm} is the neighborhood function of the best matching neuron *l* at iteration *t* and *l-m* is the distance between neurons l and m on the map grid; and σ is the width of the topological neighborhood. The training steps are repeated until convergence. After the SOM network is constructed, the homogeneous regions i.e., clusters, is defined on the map.

To evaluate the performance of clustering results produced by the SOM neural network, the silhouette coefficients are used as the measure of cluster validity [11]. The Silhouette coefficient of a cluster can indicate the degree of similarity of stations within a cluster, which is defined as [11]:

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$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{5}$$

where S(i) is the silhouette of piezometer i, a(i) measured as a Euclidean distance, is the average dissimilarity of cluster i to all other piezometers in cluster A; and b(i) is the least average dissimilarity of piezometer i to the piezometers within a cluster different from cluster A. Thus, a smaller S(i) value indicates a better similarity among piezometers within the same cluster. The overall quality of a clustering distribution can then be measured using the average silhouette width for the entire data set [11].

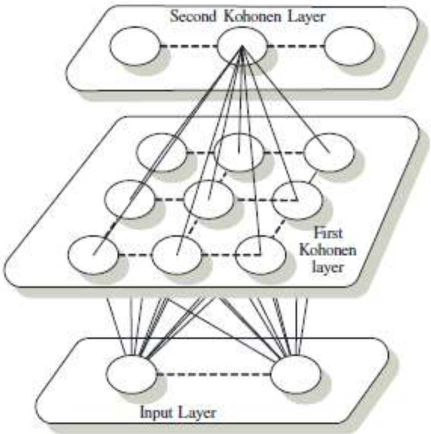


Fig. 2. Architecture of the two-level SOM neural network.

IV. STUDY REGION AND DATA

A. Study Region

Ardabil Plain (38° 03'-38°27' N and 47°55'-48°20' E) located in the north-western Iran, covers an area of about 990 km^2 (see Fig.3.). There are two high mountains locate d around the Ardabil Plain, which are Alborz and Sabalan Mountains. The mean areal annual rainfall over the semi-arid Ardebil plain is about 304 mm. May and August are known as the wettest and driest months of the region, respectively. The mean temperature in the Ardabil plain is about 9° C, and this plain is well known as the coldest region of Iran. The average number of freezing days in the Ardebil plain is about 130 days in a year. Fig. 1 represents the locations of groundwater level's stations in the study area.

In the plain, 19 piezometery stations are operated to measure groundwater level (P1, P2, P3, ..., P19). The data sampling has been reported in one-month interval at all of the piezometers. The Plain is equipped with one stream gauge at the outlet and 6 rain gauges within the watershed. Fig. 3. shows the position of piezometery stations as well as rainfall and runoff stations. The monthly rainfall, runoff and groundwater level data are available for the water years of 22 years from 1988 to 2011.

B. Model Precision Evaluation

Input and output variables for modeling purpose are usually normalized by scaling between zero and one to eliminate their dimensions. The following simple linear mapping of the variables is the most common method for this purpose [21]:

$$r_i = \frac{I_i - I_{\min}}{I_{\max} - I_{\min}} \tag{6}$$

where, I_i is the actual value and is the respective normalized value. $I_{\min}$ and $I_{\max}$ are the minimum and maximum of the values, respectively.

The normalized data were divided into training and verification sets. Typically, about 3.5 years data are used for the model training, and the remaining 1.5 years data are used for validation purposes.

In this study, two different criteria are used to measure the efficiency of the proposed methodology; the Root Mean Square Error (RMSE), and the Determination Coefficient (DC) [22].The RMSE and DC demonstrate discrepancies between predictions and observations. They are defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(I_i - \hat{I}_i)^2}{n}} \tag{7}$$

$$DC = 1 - \frac{\sum_{i=1}^{n}(I_i - \hat{I}_i)^2}{\sum_{i=1}^{n}(I_i - \bar{I}_i)^2} \tag{8}$$

In (7) and (8), n is the data number, I_i and $\hat{I}_i$ are the observed data and the calculated values, respectively, and $\bar{I}_i$ is the averaged value of the observed data. In a best model, DC and RMSE go to one and zero, respectively.\

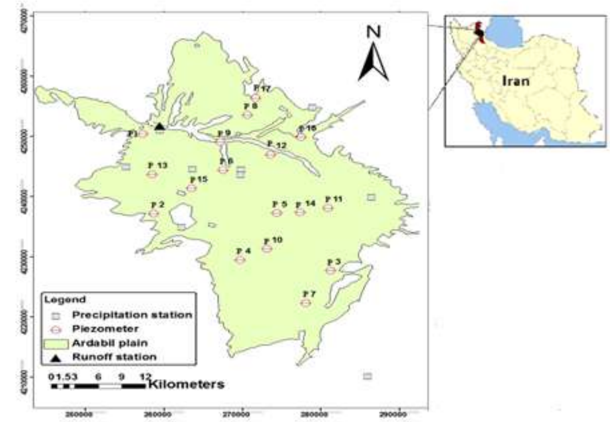


Fig. 3. Study area map with positions of piezometers.

V. RESULTS AND DISCUSSION

Due to the existence of various piezmeters over the Ardabil Plain and the importance of managing groundwater resources, it is a necessity to unite the adequate information about GWL in various regions of plain and identify the dominant piezometers to predict GWL in future. In order to accomplish the purpose two approaches in field of neural network has been utilized.

By combining the SOM as a clustering method to identify similar and predominant piezometers and ANN as a tool to capture the nonlinear underlying pattern involved at intricate data sets, an effective GWL forecasting model has been proposed in current study. The proposed model contained two stages.

At first stage, a 2-dimensional SOM was applied to classify the piezometers into the classes with similar GWL pattern. The purpose of such a 2-dimensional SOM clustering was to have an overview on homogeneous regions and approximate number of clusters with regard to the plain topology. At the second step, in order to be ensured of the highlighted clusters, a 1-dimensional SOM was applied to classify the piezometric stations with specific numbers determined at the first step. At this step the numbers of neurons in the Kohonen layer is set equal to the number of clusters determined in the first step.

Afterward, the Euclidean distance criterion was utilized to select the centriod piezometer of each cluster which is the best representative of the GWL pattern within the cluster. Sensitivity analysis was performed over the various SOM clusters with diverse data sets as inputs. Firstly, the GWL data of 17 piezometers were applied as input data to the SOM. Secondly, the combination of GWL data and UTM data of each piezometer were put to use in SOM as a multivariate clustering data. In both sorts of input variables the clustering approach were investigated by normalized and non-normalized data. The results in Table I revealed that the utilization of multivariate data in clustering did not lead to highly distinct results in comparing with the individual variable (solely GWL) data set, thus it is instructive to utilize GWL data individually as input data of clustering. K-Means method was utilized in order to verify the SOM clustering results. To evaluate the performance of the clustering results produced by the SOM and K-Means, the Silhouette coefficient was used as the measure of cluster validity. The values of Silhouette for both SOM and K-Means methods are equal, which confirm the correctness of the clustering. The consequences led to selection of 1 by 3 Kohonen layer grid with normalized data of GWL (see Fig.4.). Subsequently the centroid piezometers were determined by Euclidean distance criterion. The central piezometers are the representative of GWL in various region of plain. Thus, the specific measures should be devoted on protection and maintaining such important piezometers in order to have precise and reliable data for predictions and management of plain. At the second stage, an ANN was trained for each of the representative piezometer to predict the GWL one month ahead. The model operates based on input data consist of rainfall and runoff amount at present month and GWL values of previous month. It is noticeable that the reason of such input order lies on sensitivity analysis over the various inputs especially the GWL lags which handle seasonality and autoregressive characteristics. The considerable fact was that the model efficiency did not alter excessively in cases other than one month lag. Therefore, in order to attain the appropriate results the minimum numbers of input data were selected to reduce the error possibility to minimum. The efficiency of the trained models was tested by the verification data. The results are depicted in Table II. Fig.4. compares the observed and computed GWL in representative piezometers.

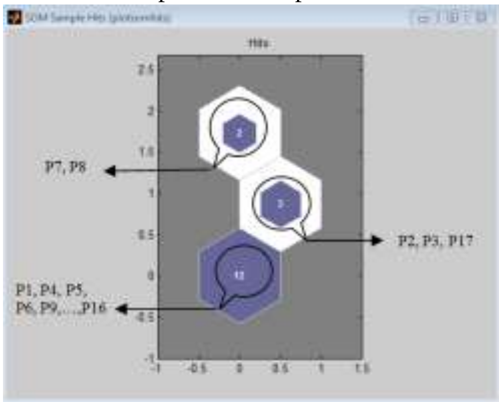
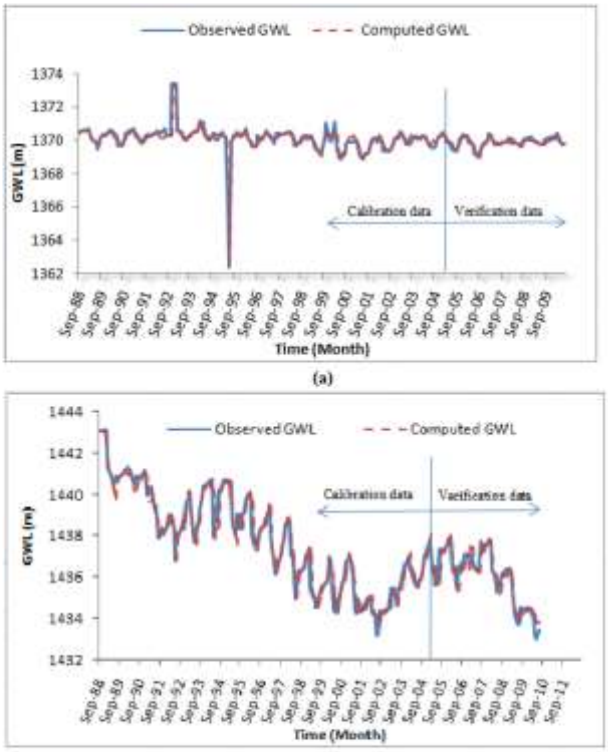


Fig. 4. 1-D SOM clustering results for normalized GWL data



(a)

(b)

Fig. 5. The observed and computed GWL values in the representative piezometer (a) P2, (b) P7.

Table I. SOM clustering results

	Applied data	SOM Clustered Piezometers	Silhouette Coefficient SOM	Silhouette Coefficient K-Means
Normalized	**GWL**	**2,3,17** **1,4,5,6,9,..,16** **7,8**	**0.87**	**0.87**
	GWL & UTM	2,3,17 1,4,5,6,9,..,16 7,8	0.85	0.85
Non-Normalized	GWL	2,3,17 1,4,5,6,9,..,16 7,8	0.87	0.87
	GWL & UTM	8,9,12,16,17 1,2,6,13,15 3,4,5,7,10,11,14	0.66	0.64

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Table II. Results and structures of FFNN model

[a]Piezometer	[b]Network structure	DC Train	DC Verify	RMSE Train(m)	RMSE Verify(m)
P2	3/3/2001	0.77	0.68	0.00027	0.00011
P5	3/9/2001	0.97	0.62	0.00055	0.00056
P7	3/5/2001	0.95	0.86	0.00033	0.00032

COMB: G(t-1): GWL with 1-month lag, I(t): Precipitation, Q(t); Runoff

[b] first, second and third number present input variable, hide neurons and output variable, respectively.

VI. CONCLUSION

In this study the SOM, FFNN approaches were combined in order to develop a hybrid black box model for the multivariate GWL simulation of Ardabil Plain located in North-West Iran. First, an unsupervised neural network technique (i.e., SOM) was applied to distinguish the similar piezometeric data and subsequently the dominant piezometer in each cluster, which detect the best GWL pattern of the region. The proper piezometer selection of SOM led to determination of regions with similar GWL in plain and also had this advantage that the groundwater related managements can be done sufficiently in future because of the data which are reported in good quality, the reason lies on a fact that by selection of permanent piezometers more equipment and investments on dominant piezometeres can be devoted in order to have good performance in recording data. The FFNN GWL prediction model was constructed to find the non-linear relationship among the lagged GWL data with rainfall-runoff data. Overall, the results provide promising evidence in comparing the observed and predicted GWL. In order to complete the current study, it is recommended to use the presented methodology to forecast the GWL by adding other hydrological time series and variables (e.g., temperature or/and evapotranspiration) to the input layer of the model or augmentation of land use effects on the GWL at adjacent piezometers. Moreover, according to the uncertainty of the rainfall process and the ability of the Fuzzy concept in handling uncertainties, the conjunction of the ANN and FIS (Fuzzy Inference System) models, as an ANFIS (Adaptive Neural-Fuzzy Inference system) model could be a reliable choice for the model progress.

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Vahid Nourani was born in Tabriz, Iran in 1975 and received his B.Sc. and M.S. degrees in Civil Engineering from University of Tabriz, Iran in 1998 and 2000, respectively. He then continued his graduate study in Civil and Environmental Engineering in the field of Hydrology at Shiraz University, Iran and Tohoku University, Japan and was graduated in 2005. Nourani was with the Faculty of Civil Engineering, University of Tabriz as an Assistant Professor from 2005-2009; as Associate Professor from 2009-2011 and with Dept. of Civil Eng., University of Minnesota, USA at 2011 and in this period, 35 Ph.D. and M.Sc. students were graduated under his technical supervision. His research interests include rainfall-runoff modeling, Artificial Intelligence applications to water resources engineering, Hydro informatics and computational hydraulics. His researches outcomes have been published as 34 Journal articles, 1 book, 2 book chapters and more than 45 papers presented in international and national conferences. He is currently researching about Geostatistics and 2-D wavelet transform applications to hydrological simulations.