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Groundwater Level Forecasting by Application of Artificial Neural Network Approach: A Case Study in Qom Plain, Iran

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ABSTRACT

Groundwater plays an important role in providing water supply especially in arid and semi-arid regions such as Iran. Given globally water crisis, monitoring and analyzing water levels can help water resources managers and planners for sustainable utilization and management of water supplies. On the other hand, groundwater processes exhibit dynamic, temporal and spatial patterns; making groundwater fluctuation modeling a complex and challenging task. Among different modeling methods, artificial neural networks (ANNs) are regularly used for complicated problems due to their distinctive and powerful properties. Qom plain in Iran is an arid region whose groundwater utilization in the last decades has led to downfall in water table. In this study groundwater level fluctuations were investigated in two distinct wells in this region using monthly groundwater level data recorded for 11 years. For modeling, the ground water time series of each studied well were entered as the input and output to the network and Time delay neural networks (TDNN) with various network structures and input delays were used for achieving the best results. The findings of the best modeling structure represented fair fitting for forecasted results in comparison with observed data, hereby underlining the promising application of this method for groundwater level modeling.

1. Introduction

The analysis of long-term regional groundwater level measurement provide a better understanding of the causes of groundwater level (GWL) fluctuations in aquifers, and therefore improve the knowledge behind the variability of GWLs (Chang et al., 2016). The GWLs vary for many reasons; some due to natural phenomena and others because of human activities. The changes in water level can be divided into several categories. The fluctuations occur generally due to one of the following three major factors: changes in the volume of water stored in the aquifer, changes in atmospheric pressure and changes caused by aquifer deformation (Nakhaei et al., 2012). Detailed assessments of GWLs enable water managers, engineers, and stakeholders to: (i) develop better strategies to avoid or reduce adverse effects such as loss of pumpage in residential water supply wells, land surface subsidence, and aquifer compaction; (ii) develop a better understanding of the dynamics and underlying factors affecting GWLs; and (iii) balance the needs of urban, agricultural, industrial and other demands and analyze the benefits and costs of water conservation. An important component of this is to forecast accurately the GWL (Adamowski and Chan, 2011).Although conceptually and physically-based models are the main tools used to foster an understanding of the physical processes taking place in a given system, there are however practical limitations on account of data insufficiency and modeling time (Daliakopoulos et al., 2005; Maheswaran and khosa, 2013). A dynamically predictive model that can tackle the persistent trend and time-variant behavior of hydrological variables is desirable for the efficient planning and management of water resources. Under such circumstances, empirical models such as regression and artificial neural network (ANN) models serve as attractive alternatives, because they can provide useful results applying relatively fewer data, and are less laborious and therefore cost-effective (Sahoo and Jha 2013). Soft-computing models were mainly developed to explore the input-output patterns in groundwater data to make accurate estimation and/or forecasts. The ANNs, a promising soft computing method, can effectively capture the spatial-temporal characteristics of patterns at different scales for accurately imitating dynamic complex systems with less computational requirements (Sahoo and Jha 2013). Unlike physically-based numerical models, the ANNs require neither explicit characterization nor quantification of physical properties or accurate representation of the governing physical laws (Coppola et al. 2005). In general, the advantages of ANNs over other statistical and conceptual models are:

1) The application of ANNs needs no previous knowledge of the process because the ANNs have black-box properties.

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2) The ANNs have the intrinsic property of nonlinearity since neurons activate a nonlinear filter called an activation function.
3) The ANNs can have multiple inputs with different characteristics, enabling ANNs to represent the time-space variability.
4) The ANNs have the adaptability to represent change of problem environments (Nourani et al., 2009).

A number of studies used various soft computing techniques for modeling groundwater time series. In the recent years, the ANN has been used to predict the GWL (e.g., Adamowski and Chan, 2011; Daliakopoulos et al., 2005; Mohanty et al., 2013, 2015; Nourani and Mousavi, 2016; Sahoo and Jha 2013; Sethi et al. 2010).

2. Methods and Data

2.1. Study area

Qom plain is located between latitudes 34° 27′ N and 34° 42′ N and longitudes 50° 49′ E to 51° 11′ E in the central Iran, politically in Qom province, where is a part of central desert watershed in Iran (Ebrahimiet al., 2016). The study area is under the influence of a hot and dry climate. The annual mean temperature is around 18.1°C and varies between 5.2°C in January and 31.6°C in July. The mean annual precipitation of the Qom province is 161mm. Qom plain as an arid area is surrounded by two different landscapes; the combination of highlands and fluvial plains in the west and northwest, and salt crust (NamakLake), alluvial plains and sand fields in the east and southeast. The Namak Lake is the lowest point and desert pavements are major types in alluvial fans. Other features of the study area are the lack of any permanent river, and very little water discharge from seasonal streams, so that it is totally used in upper lands to irrigate, or to feed aquifers (Ebrahimiet al., 2016).

In the dry land of Qom, the groundwater as a critical factor supports the agricultural activities during the deficiency of precipitation. Over the course of the past two decades, Qom plain has experienced a sharp drop in GWL and water quality degradation, mainly due to the reduction in stream flows and excessive pumping from agricultural wells (Zehtabian et al., 2002). Because the rainfall is low, the seasonal stream flows have an important role in feeding aquifers (Ebrahimiet al., 2016). The decline in GWL in the study area is shown in Figure 1.

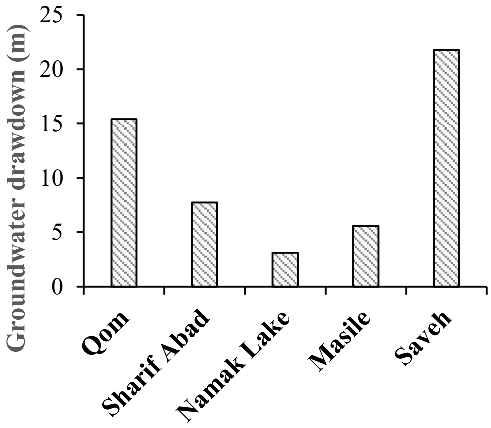

Fig. 1. Decline in (off) groundwater level in study areas

2.2. Artificial neural networks

The ANNs are inspired by the learning processes taking place in biological systems. The ANN is composed of many artificial neurons linked together according to specific network architecture. A neural network can be used to predict future values of possibly noisy multivariate time-series based on past histories, and it can be described as a network of simple processing nodes or neurons, interconnected to each other in a specific order, performing simple numerical manipulations. The objective of the neural network is to transform the inputs into meaningful outputs (Adamowski and Chan, 2011).

It is necessary to design the ANN properly to execute the function of biological neurons artificially. Hence, the ANN designing (or ANN models) follows a systematic procedure involving five basics steps: (1) selection of influential inputs; (2) selecting suitable ANN architecture; (3) building the neural network; (4) training and testing of the developed ANN models; and (5) evaluating the performance of the ANN models (Sahoo and Jha 2013).

2.3. Time Delay Neural Network (TDNN) model

The ANNs can be used to predict future values of possibly noisy time series based on past histories. The ANNs are classified into static and dynamic categories. The difference between these two networks is related to their training styles. The static networks have no feedback elements and contain no delays; the output is calculated directly from the input through feed-forward connections. In other words, the order of inputs in the static networks is not important and has no effect on the outputs, while the output in the dynamic networks depends not only on the current input to the network, but also on the current or previous inputs, outputs, or states of the network (Beale et al., 2010). The TDNN is a feed-forward dynamic network including several layers of the network, which is commonly used in time-series modeling. When using TDNN, the network automatically scales inputs and targets so that they fall in the range [-1,1]. After training, the TDNN converts the output back into the original units. In this case, the prediction of future values of a time series *Y(t)* is done from past values of a second time series *X(t)*and it is possible that *Y(t)=X(t)*. It can be written as follows (Beale et al., 2010):

$$y_{t+1} = f\,(x_t,\ x_{t-1},\ \ldots,\ x_{t-d}) \tag{1}$$

Where, *d* is the desired delays, *x* is the input and *y* is the output time series. The TDNN model used in this study is a three-layer feed-forward network with tangent-sigmoid transfer function in the hidden layer and linear transfer function in the output layer. Figure 2 shows the architecture of this network. The architecture 3-3-1, for example, means 3 input time series, 3 hidden nodes and 1 output node. It should be noted that the random sampling involves sequences of data; i.e., during the training, validating and testing of the network, the true inputs and the true output are available.

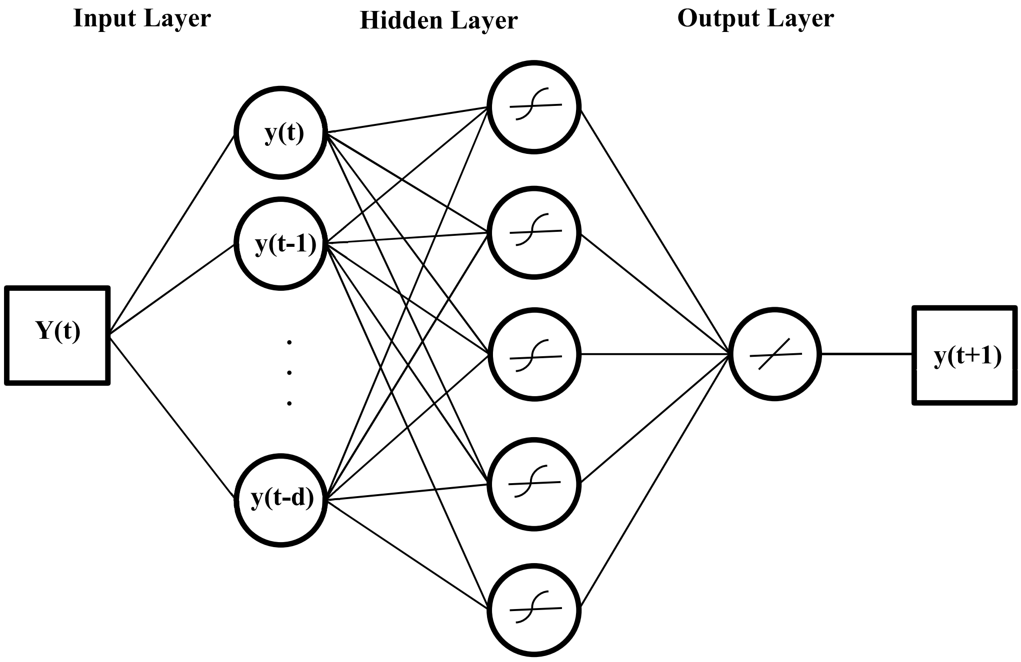

Fig. 2. Three layer TDNN architecture with a delay of d and five neurons in the hidden layer.

The application of TDNN for forecasting GWL consists of two steps. The first step is training, validating and testing the model and the second one is to apply the model for prediction. In the first step, several important items should be considered, such as the TDNN architecture, the number of delays and the number of neurons in hidden layer, which are determined by trial-and-error procedure.

3. Results and discussion

The data were obtained from the two wells located at Qom plain, which were employed to create the model applied in this study. The ANN model for GWL forecasting were developed using the MATLAB R2012 software program.

Table 1 shows the characteristics of the two wells. The data used are monthly measurements of the GWL at each well for 11 years with a month interval. The data of earlier ten years were used for creating the model and the next year data for comparison with the simulated values using the models. In the ANN model (based on the structure of the models), the data of first ten years were randomly divided into three subsets: 70% to train, 15% to validate that the model is generalizing and to stop training before overfitting and 15% as a test of model generalization (Beale et al., 2010). Random data selection involves sequences of data.

Table 1. Characteristics of the two study wells.

Well No	Well Name	GWL recording period	Number of the total data
1	Zanbo urak	Monthly 2002-2013	132
2	Seraje	Monthly 2002-2013	132

It should be noted that, for good performance of ANN models, there should be relatively similar statistical characteristics between training, validating and testing sets.

According to the randomly consideration of the training, validating and testing sets, the statistical characteristics of the three sets are likely similar, and reasonably the accuracy of the model will increase (Ebrahimi et al., 2016).

The GWL time series of each well were entered as the input and output to the TDNN model. In this case, the models were trained considering the current step of a time series as a function of previous steps of the same time series. For obtaining the best results, different network architectures and various delays were applied. The delays were examined from 1 to 6 months. Once the model training is completed, it can be used to predict next values. The best TDNN model is the one with the lowest error (Ebrahimi et al., 2016).

Using different model structures and various input delays, the TDNN model was trained to simulate the GWL of the wells 1 and 2. Figures 3 and 4 show the observed GWL with the simulated GWL during the simulating period at the wells 1 and 2, respectively, for TDNN model.

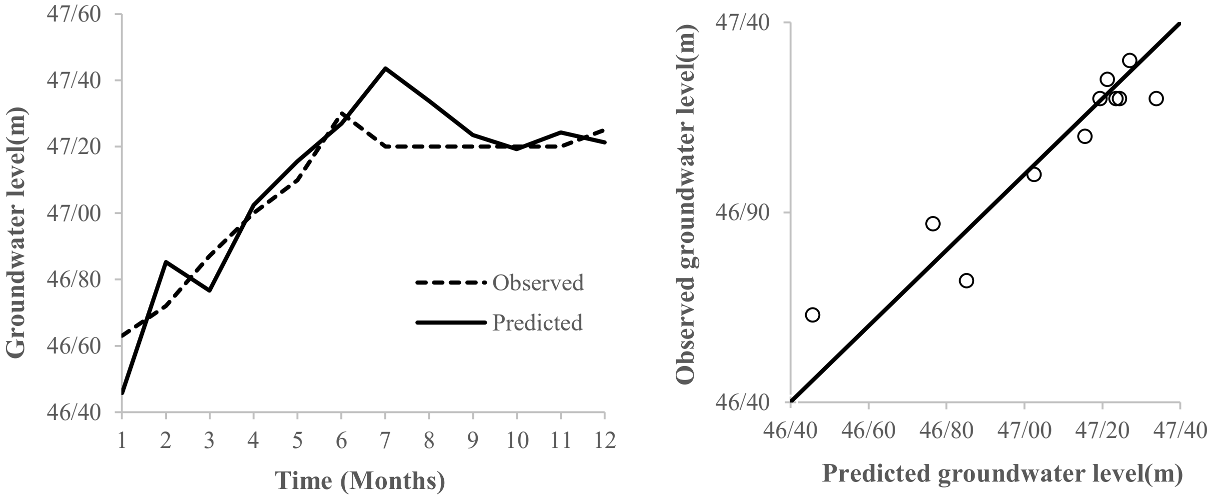

Fig. 3. Comparison of simulated versus observed GWL at well 1 using TDNN model.

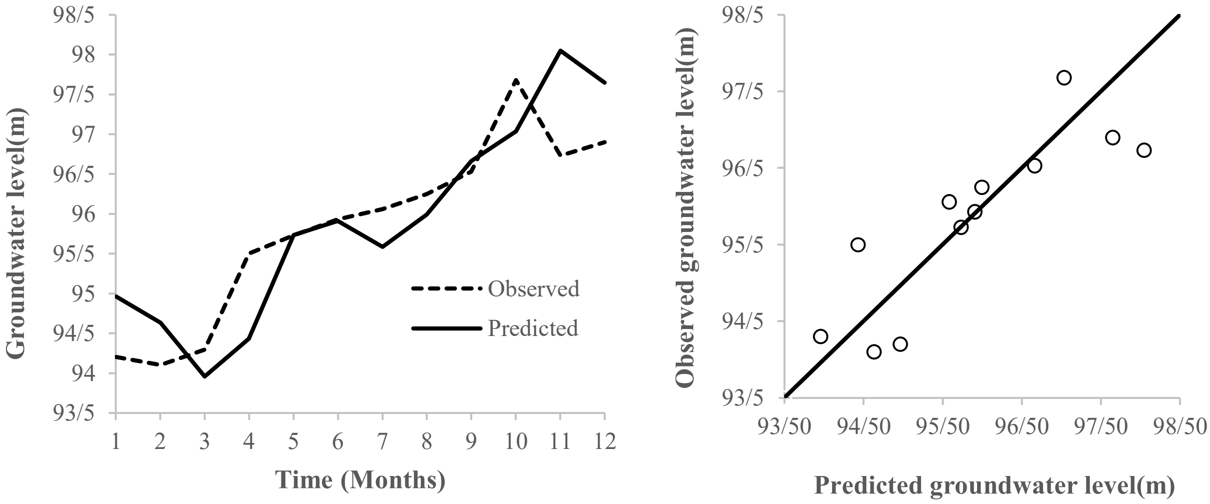

Fig. 4. Comparison of simulated versus observed GWL at well 2 using TDNN model.

4. Conclusion

In this paper, the ANN model is used for forecasting GWL fluctuation in Qom plain, Iran. The TDNN models for GWL forecasting for both wells were developed using MATLAB R2012 software program. The purpose of this research was to evaluate the ANN as a potential tool for predicting GWL. The ANN models were trained and tested based on different combinations of time series and numbers of neurons in the model's hidden layer. The applied model was able to forecast monthly GWLs in the study area in advance with a reasonable accuracy. As a future scope, the effect of different variables like seasonal precipitation, run off from seasonal rivers and pumping from agricultural wells can be explored for other case studies where these would influence the GWLs. Also, the application and comparison of other methods like wavelet analysis, multiple linear regression and support vector regression (SVR) analysis can be explored for long-term prediction.

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