Estimation of ground water level in Jahrom plain, using Artificial Neural Networks

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Abstract
This paper is arranged to estimate the ground water level in Jahrom plain, using Artificial Neural Networks. For this purpose, Artificial Neural Networks (ANNs) with nonlinear activation functions (Logsig or Tansig) were applied. Also, the collected data of Jahrom plain wells in Fars province were used. In this plain, 192 data of monthly average ground water level in 16 years were collected. In addition to ground water level, 4 monthly average parameters: precipitation, moisture, evapotranspiration and temperature were taken into account. These parameters are effective on ground water level. Four statistical parameters (mean square error, relative standard error, scatter index and correlation coefficient) were used to assess the ANN models. Finally, very satisfactory results of the ANNs were obtained.

Keywords:
Artificial Neural Networks (ANNs), Jahrom plain, ground water level and Activation function.

1. Introduction

The groundwater system is very complex; in other words, this nonlinear system is affected by many parameters. Thus, the prediction of the ground water level is very difficult.
Stochastic models are based on observational data can be a good choice in forecasting groundwater level.
Artificial neural network models are powerful and effective tools for solving nonlinear models. Thus these models are useful for hydrological applications.
Artificial neural networks haven't complex mathematical formula. This advantage of artificial neural networks is caused that these models as an effective tool can be used in modeling of groundwater level (Rizzo and Dougherty 1994 and Ranjithan et al. 1995).
Today, indiscriminate exploitation of groundwater is a major challenge, especially in developing countries. Also, groundwater resources are influenced by Population Growth. Thus, predicted level of ground water table is very important for proper management of underground aquifers.
Shigidi and Garcia (2003) applied an artificial neural network to model the ground water level. They obtained the complex relationship between transfer coefficient and groundwater level.
Coppola et al. (2003) used an artificial neural network model to predict the ground water level. This ANN model is found to give significantly better agreements with the measured data in comparison with the numerical models.
Several structures of artificial neural networks were applied to estimate the ground water level by Coppola et al. (2005). The obtained results showed that the Levenberg–Marquardt algorithm (LMA) is more accurate than other training methods.
Jianqiang and Xianxiang (2001) presented a predictive model to determine the groundwater level based on radial basis function neural network.
In this research work, the artificial neural networks are used to predict the groundwater level in Jahrom plain. The ANN models are first trained and tested using input and output data sets. The performance of these ANN models is then validated with various statistical parameters.

2. Material and methods

Case study: Jahrom plain

Jahrom plain is located at the southeast of Fars province that is one of subbasins of Mond river. This plain is one of the most fertile plains. The cachment area of this plain is 1016 square kilometers. Jahrom plain has a warm/dry climate with hot summers and mild winters.
In this research work, the measured data of Jahrom plain are used to estimate the ground water levels.
These data (5 monthly average parameters: ground water level, precipitation, moisture, evapotranspiration and temperature) were collected in 1998-2010.

Artificial Neural Networks

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This type of model has a very high number of parameters. Therefore artificial neural network is very flexible.
The input and output data sets were first normalized. The ANN models are then trained and tested using input and output data sets. It should be mentioned that 75 percentage of the data set was randomly chosen for the training process and the remaining percentage was used for the testing process.

In this research work, the training process was carried out using a Back-Propagation algorithm.
Purelin was considered as the transfer function of the output layer. Also, Logsig or Tansig transfer functions was applied for single hidden layer.
Artificial neural networks were modeled using Eq. (1). Thus, it can be shown that:

$$W_{t+1} \cong f\left(P_t, H_t, E_t, T_t\right) \quad (1)$$

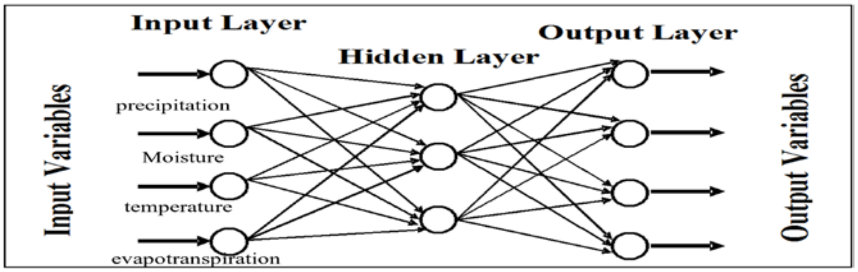

Fig. 1. The feed-forward artificial neural network structure in this study

Where $W_t =$ predicted ground water level, $P_t =$ precipitation, $H_t =$ moisture, $E_t =$ evapotranspiration, $T_t =$ temperature and $f =$ functional symbol.
The basic structure of such a used network is schematically given in Fig. 1.

3. Results and discussion

Four statistical parameters (Mean Square Error (MSE), Relative Standard Error (RSE), Scatter Index (SI) and Correlation Coefficient (R2)) were used to assess the back-propagation neural networks.

Table 1. Main statistical parameters for ANN models (with Logsig transfer function in hidden layer)

Case Number			1	2	3	4	5	6
Neurons number for hidden layer			5	8	**9**	10	15	20
statistical parameters	MSE	Train	0.079	0.0792	**0.071**	0.0717	0.0712	0.0715
		Test	0.1061	0.0981	**0.0969**	0.0976	0.0973	0.1015
	SI	Train	0.555	0.559	**0.514**	0.519	0.517	0.542
		Test	0.637	0.616	**0.610**	0.612	0.610	0.629
	RSE	Train	0.238	0.238	**0.206**	0.211	0.211	0.233
		Test	0.307	0.291	**0.282**	0.287	0.286	0.311
	R^2	Train	0.809	0.807	**0.831**	0.822	0.827	0.812
		Test	0.768	0.784	**0.791**	0.784	0.788	0.775

The results of multilayer feed-forward ANNs are shown in Tables 1 and 2, for both training and testing processes. It should be mentioned that these tables are obtained for Logsig and Tansig transfer functions, respectively

As shown in Tables 1 and 2, Logsig activation function has more accurate results compared to Tansig transfer function.
Table 1 shows that the third case is the best ANN model for estimating the groundwater level. This model has 9 neurons in the single hidden layer.

Table 2. Main statistical parameters for ANN models (with Tansig transfer function in hidden layer)

Case Number			1	2	3	4	5	6
Neurons number for hidden layer			5	6	**7**	10	15	20
statistical parameters	MSE	Train	0.087	0.0872	**0.079**	0.0797	0.0792	0.0795
		Test	0.1141	0.1061	**0.1049**	0.1056	0.1053	0.1095
	SI	Train	0.583	0.587	**0.542**	0.547	0.545	0.57
		Test	0.665	0.644	**0.638**	0.64	0.638	0.657
	RSE	Train	0.254	0.254	**0.222**	0.227	0.227	0.249
		Test	0.3230	0.307	**0.298**	0.303	0.302	0.327
	R^2	Train	0.796	0.794	**0.818**	0.809	0.814	0.799
		Test	0.755	0.771	**0.778**	0.771	0.775	0.762

Also, this ANN model (case 3 in Table 2) is found to give significantly better agreements with the measured data in comparison with the other cases. This case has 7 neurons in the single hidden layer. In other words, for Logsig transfer function, the best result is obtained with more number of neurons in comparison with Tansig transfer function.

Also, Figures 2 and 3 show the back-propagation neural networks simulated data versus measured groundwater levels for training and testing data sets, respectively. These figures are drawn for best cases of Tables 1 and 2.

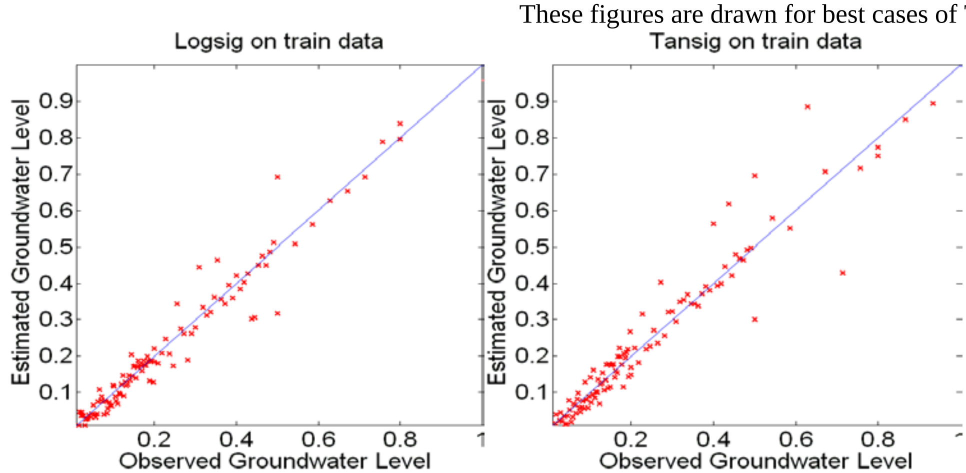

Fig. 2. Scattering plots for training data (for best case)

It is seen from Figs. 1 and 2 that the measured values of groundwater level are closer to those predicted by ANN model with Logsig activation function than to those predicted by ANN model with Tansig activation function.

This simplified mathematical model has the ability to learn and train from the examples and analysis of the complex problems. Thus, in this study, MLP-ANNs were developed to predict monthly average ground water levels in Jahrom plain.

4. Summary and conclusions

In the last two decades an increasing interest can be observed for predictive algorithms such as artificial neural networks.

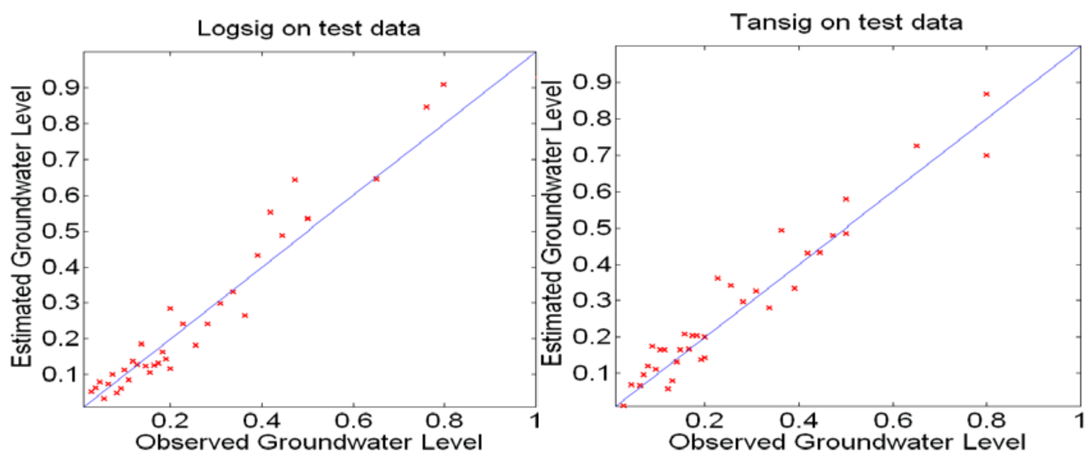

Fig. 3. Scattering plots for testing data (for best case)

The obtained results showed that a MLP-ANN with Logsig transfer function and 9 neurons in the single hidden layer is the best ANN model for estimating the ground water level.
For Logsig transfer function, the correlation coefficient R^2 for training and testing data is equal to 0.831 and 0.791, respectively.
For Tansig transfer function, an ANN with 7 neurons in the single hidden layer is the best ANN model. the correlation coefficient of this model for training and testing data is equal to 0.818 and 0.778, respectively.
In other words, Logsig activation function has more accurate results compared to Tansig transfer function.

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