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Application of Artificial Neural Network for Groundwater Level Simulation in Amritsar and Gurdaspur Districts of Punjab, India

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Abstract

In this paper, the most stable and efficient neural network configuration for predicting groundwater level in Amritsar and Gurdaspur districts of Punjab, India is identified. For predicting the model efficiency and accuracy, different types of network architectures and training algorithms are investigated and compared. It has been found that accurate predictions can be achieved with a standard feed forward neural network trained with the Levenberg–Marquardt algorithm providing the best results. Good estimation of groundwater level can be achieved by dividing the boreholes/observation wells into different groups of data and designing distinct networks which is validated by the ANN technique and the degree of accuracy of the ANN model in groundwater level forecasting is within acceptable limits. The ANN method has been found to forecast groundwater level in Amritsar and Gurdaspur districts of Punjab, India.

Keywords: Artificial neural networks; Groundwater level forecasting; Amritsar; Gurdaspur; Punjab; Aquifer exploitation

Introduction

Groundwater always has been as one important and reliable resource to supply drinking and agriculture water and considered to be a reliable resource for supplying consumption needs of different users [1]. Groundwater Reservoir also called 'aquifer' is a complicated system and is exposed to either natural or artificial stresses on the aquifer in different chronological levels resulting in the fluctuations of groundwater level. Thus, to exploit and manage groundwater, mathematical models are needed to predict groundwater level fluctuations. Conceptual and physically-based models are considered to be the main tools for depicting hydrological variables and understanding the physical processes taking place in a system [2] but they do have practical limitations. When data are not sufficient, getting accurate predictions is more important than conceiving the actual physics. Empirical models remain a good alternative method and generally provide useful results without a costly calibration time [3]. Artificial Neural Network (ANN) models are such 'black box' models with particular properties which are greatly suited to dynamic nonlinear system modeling [4]. ANN has proven to be an extremely useful method for modeling and forecasting of hydrological variables/processes [5-8].

Coppola et al. [9] showed that ANN has potential in accurately predicting of groundwater level fluctuations in an unsteady state of an aquifer influenced by pump and different weather conditions. They noted that predicted results of ANN are more accurate than quantitative models and also showed that ANN models are good at simulating karstic and leaky aquifers where other numerical models are weak in such cases.

In another study by Taiyuan et al. [10] the effects of hydrological, weather and humidity conditions on groundwater level were simulated by neural networks in lower part of Shenyang river basin, North West of china. The used ANN model was able to predict groundwater level with the average error of 0.37 m or lower with the high accuracy. Nadiri [11] had dealt with evaluating of artificial neural network (FFN-LM) ability in modeling of complex aquifer of Tabriz.

In this paper, an attempt has been made to identify the most stable and efficient neural network configuration for predicting groundwater level in the Amritsar and Gurdaspur districts of Punjab. The main purpose of this article is to use artificial neural networks especially feed forward back propagation neural networks to simulate and predict groundwater level. Amritsar and Gurdaspur districts of Punjab were chosen as the study area as the groundwater resources have been overexploited in Punjab including Amritsar and Gurdaspur districts during the last two decades. The groundwater level and quality in Punjab have been decreasing steadily as discussed in numerous studies carried out in different parts of Punjab and Indo-Gangetic basin by various researchers [12-34]. For the planning and management of groundwater resources in the region timely and accurate enough forecasts of ground water levels are required. Therefore, ANN technique was used for simulating the groundwater levels in Amritsar and Gurdaspur districts based on groundwater level data of 4 observation wells in 4 blocks namely Ajnala, Majitha, Rayya and Tarsika of Amritsar and 8 observation wells in 8 blocks namely Batala, Dera Baba Nanak, Dina Nagar, Gurdaspur, Fatehgarh Chrian, Kahmuwan, Kalanaur and Sri Hargovindpur taken from the Punjab Water Resources and Environment Directoate, Chandigarh.

The Study Area

Amritsar

Amritsar district is located in northern part of Punjab state and lies between 31° 28' 30" to 32° 03'15" north latitude & 74° 29' 30" to 75° 24' 15" east longitude and having a total area of 5056 sq.km (Figure 1) while Gurdaspur district lies between 31° 36' to 32° 34' north latitude & 74° 56' to 75° 24' east longitude and having a total area of 3513 sq.km The districts fall in between Ravi river and Beas river. The area has a semiarid climate typical of Northwestern India and experiences four seasons primarily: winter season (December to March) with temperature ranges from 0°C

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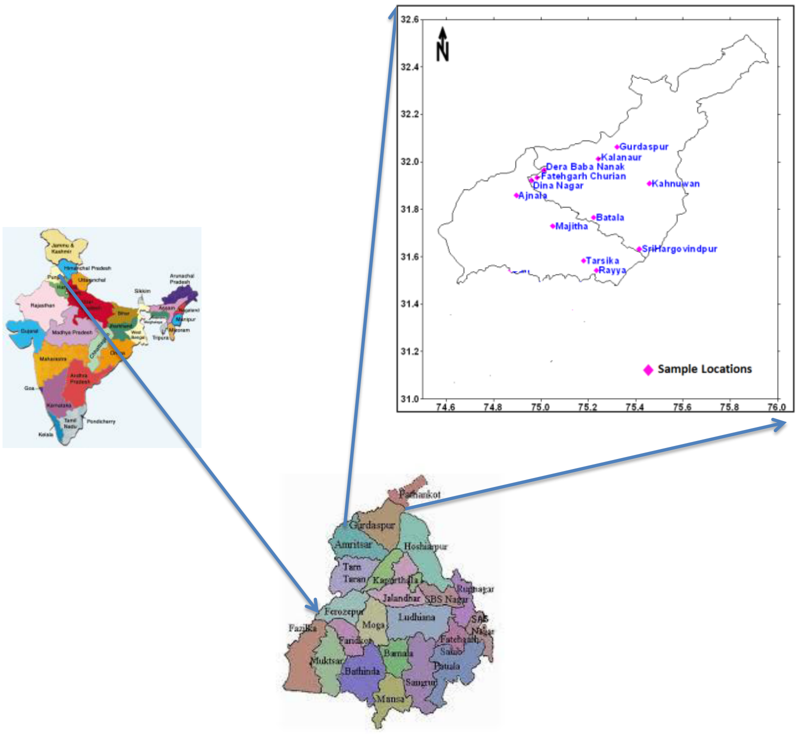

Figure 1: Study area.

to 15°C, summer season (April to June) where temperatures can reach 42°C, monsoon season (July to September) and post-monsoon season (October to November). Annual rainfall is about 681 mm in Amritsar and 1013 mm in Gurdaspur district.

Hydrogeology

The study area is a part of Upper Bari Doab. Soils in the study area are fine to coarse loamy, calcareous and are well drained. The main aquifer group is granular zone with alternate layers of thick or thin clay. The aquifer groups are laterally distributed. The total thickness of the alluvium ranges from 300-450 m and there may be 5-6 aquifers.

Data

The available data required to simulate groundwater were monthly rainfall and water level data. These data with one-month time step were introduced to the ANN as input. Water level of plain observation wells of depth of 60 m was available for 2006-2013. While, monthly rainfall data were available for the period 2006-10.

On the basis of the studies carried out by Lallahem et al. [35], Nadiri [11] and Mirarabi [36] time series data of ground water levels and rainfall have been selected for the present studies. Rainfall is considered as one of the important inputs for the ground water level forecasting model. To design network, analogues output and input data of the same period with an equivalent time step were used. Therefore, after processing the available data of water level (main goal in this study) and rainfall, the time step selected for all data is monthly.

Methodology

Artificial Neural Network (ANN)

Artificial neural networks (ANN), which operates, analogous to that of biological neurons system are getting more and more attention in the area of hydrology and water resources [37]. ANN models are basically data driven models and in hydrological context they are considered as black box models [5]. ANN models can be a good alternative to mathematical models as they have a high processing ability and can execute the future scenarios very fast. Hydrological processes are generally nonlinear in nature. The ability of ANN to model nonlinear processes advocates their use in hydrology and water resources to model various hydrological processes [6]. For the first time McCulloch and Pitts [38] presented a basic artificial neural network model. With the development of computational techniques, various researchers have suggested a different ANN structures to model various real life problems.

Studies carried out by Aziz and Wong [39], ASCE [40,41], Abd¨usselam [42], Agarwal et al. [4], Gidson [43], Hagan et al. [44], Lohani et al. [7], Taslloti [45] have demonstrated the application of ANN in rainfall –runoff modeling. In hydrological forecasting the application of ANN is very effective and the works of Jones [46], Kar et al. [47], Lohani et al. [3,8], Maier and Dandy [48] and Uddameri [49] suggested that the artificial neural networks provides an alternate and effective over the conventional methods. Previous studies have shown that ANN has shown their capability in reproducing the unknown rainfall-runoff relationship, gauge-discharge relationship, discharge-sediment relationship, [5-7] and modeling of hydrological time series [8]. Rosmina et al. [50] mentioned that the modern techniques can be applied to predict and understand the temporal and spatial relations between effective parameters in groundwater level. In order to investigate the effects of hydrological, meteorological and human factors on the ground water levels a three layer back propagation artificial neural network model was applied by the Shaoyuan et al. [51] for two regions in the Minquin oasis, located in the lower reach of Shiyang river Basin, China, Jothiprakash and Suhasini [52] demonstrated the capability of ANN model to predict ground water level in Sri ram Sagar reservoir project area, Andhra Pradesh, India, Studies carried out by Zahra and Gholamreza [53], Kavitha and Naidu [54] and Bessaih et al. [55] investigated the use of ANN to forecast ground water level.

Application of neural networks

For developing ANN model generally the data sets are required for the training, validation and testing of the ANN networks. In this study, observed rainfall data were used to train and validate an artificial neural-network. The learning algorithm called the back-propagation was applied to the single hidden layer. Scaled Conjugate Gradient (SCG), Levenberg–Marquardt (LM), Gradient Descent with Momentum (GDM), and back propagation were used for the purpose. The Neural Network has been optimized using the MATLAB Neural Network Toolbox. In the training stage, to define the output accurately, the number of neurons was increased step-by-step in the hidden layer. Inputs and outputs have been normalized in the range of (0–1) as NN works efficiently within this range. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used in hidden layer while purelinear (purelin) transfer function has been used in output layer. After the successful training of the network, the network was tested with the test data. Using the results produced by the network, statistical methods have been used to make comparisons.

Measures of prediction performance

The prediction performance of ANN model results have been investigated by the statistical methods e.g. RMSE and coefficient of determination (R^2) between network output and network target outputs in training and validation groups.

Results and Discussion

The aim of using ANN is to test the ability to predict groundwater level fluctuations in Amritsar and Gurdaspur districts of Punjab. The network has input parameters such as rainfall of current and previous two months, groundwater level of current and two previous months and one output parameter i.e. forecasted groundwater level with 6 month lead period. These monthly data were introduced to the ANN as input. Groundwater level of observation wells was available for 2006-2013.

To design networks, analogues output and input data of the same period with an equivalent step time were used. Training and validation data included for the period 2006 to 2013 for all networks. To consider the efficiency of every algorithm and reach to the best desired conditions, several parameters, and variables such as number of neurons in hidden layers, percent of dividing data into training and validation sets, learning rate, number of repeating epochs and momentum coefficient were varied. Among these conditions, number of neurons and percent of dividing data to the training and validation sets are more effective in changing conditions and reaching to a desired state of network than others are. Optimal network architecture was selected based on the minimum Root Mean Square Error (RMSE). In order to avoid overfitting of ANNs "early stopping" method has been applied.

For artificial neural network modelling input parameter-rainfall of the study area and previous month and current month water level were selected as input to the model and six month ahead water levels in observation wells were selected as output and were normalized. These parameters were scaled between zero and one. Then, to increase the predicting capability of the network, the input and output data were divided into two groups for each data set (i.e. calibration data from 2006 to 2010 and validation data from 2011 to 2013).

Validation

To validate the neural networks models, new observation data were introduced to the networks and simulated groundwater level were compared with actual groundwater of all observation wells in the study area (Figures 2 and 3). As the figures show, the neural networks can

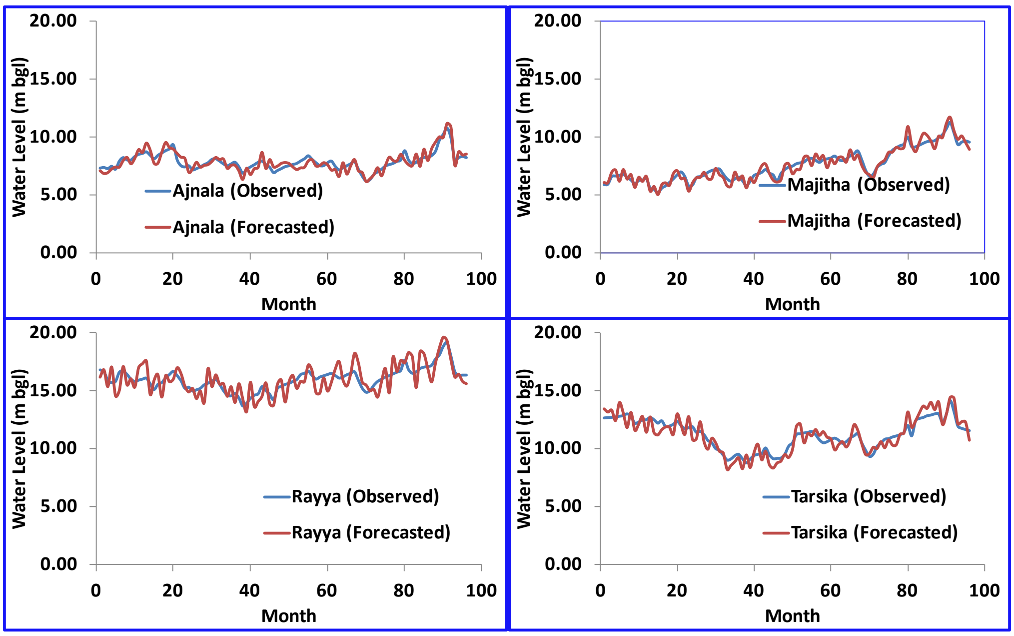

Figure 2: Observed and forecasted water level in Amritsar district (calibration, 1- 60 months and validation results, 61-96 months).

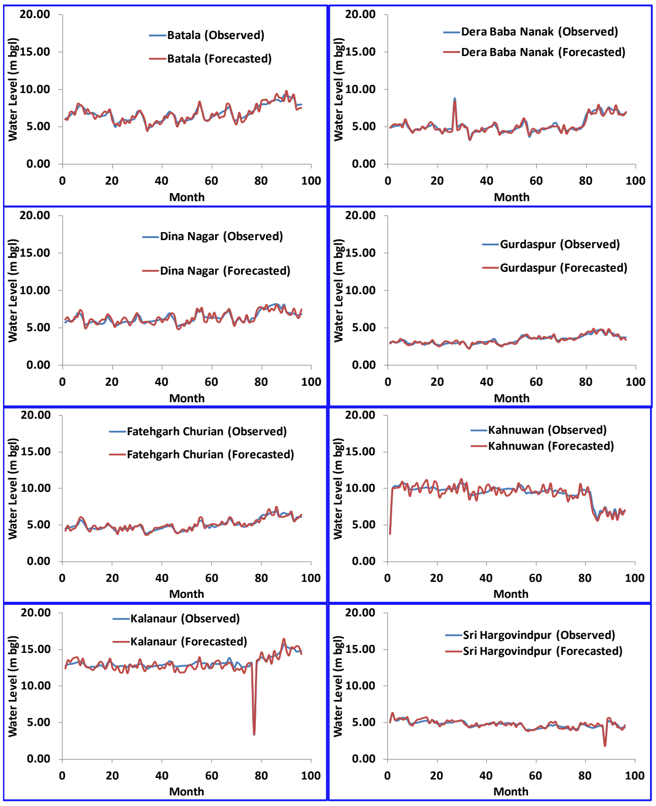

Figure 3: Observed and forecasted water level in Gurdaspur district (calibration, 1- 60 months and validation results, 61-96 months).

Model	Training		Validation	
Location	RMSE (m)	R^2	RMSE (m)	R^2
Ajnala	1.52	0.965	2.26	0.921
Majitha	1.73	0.976	2.16	0.928
Rayya	1.08	0.934	1.32	0.892
Tarsika	0.98	0.991	1.25	0.932
Dera Baba Nanak	0.31	0.934	0.42	0.906
Dina Nagar	0.38	0.958	0.51	0.932
Gurdaspur	0.20	0.868	0.39	0.827
Fatehgarh Churian	0.29	0.939	0.35	0.911
Kahnuwan	0.59	0.927	0.78	0.904
Kalanaur	0.51	0.928	0.73	0.913
Sri Hargovindpur	0.24	0.914	0.37	0.898

Table 1: RMSE and coefficient of determination.

simulate groundwater level with reasonable accuracy in most of the observation wells.

To evaluate the accuracy of the designed networks, RMSE and coefficient of determination have been computed. It is observed that (Table 1) the values of RMSE varies from 0.20 to 1.73 m during calibration and 0.35 to 2.26 m during validation. Furthermore, the coefficient of determination for both the calibration and validation data shows that the forecasted groundwater tables show reasonably good correlations.

Conclusion

The goal of this study was to evaluate the feed forward neural network as a possible tool for predicting groundwater level in Amritsar and Gurdaspur districts of Punjab. Rainfall of the study area and previous months groundwater levels were taken as input, and the future groundwater levels with six month lead period were the output. A back propagation (BP) neural network model algorithms have been studied in one hidden layers. Number of neurons on hidden layer also varied to optimize network. Based on statistical indices (R^2 and RMSE), the best networks were determined for each station (Table 1). These networks were trained with developed ANN network algorithm. To these neural networks, new observation data were introduced to the networks. Then, forecasted groundwater levels were compared with actual groundwater of all observation wells in the study area. There was a good fit between real and calculated data by considering all observation wells.

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