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Research Article

NEURAL NETWORK MODELING FOR WATER TABLE FLUCTUATIONS: A CASE STUDY ON HOSHANGABAD DISTRICT OF MADHYA PRADESH

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Abstract- The accurate prediction of groundwater level is quite essential for ecological and sustainable development and management of groundwater resources. In this study artificial neural networks, namely multilayer perceptron (MLP) was used for predicting water tables in a selected aquifer system. The inputs for the ANN models consisted of rainfall, temperature and river stage and water table data. The ANN model was trained using gradient descent with momentum (GDM) algorithm. The predictive ability of ANN model was developed for each of the seven sites was evaluated using four statistical indicators (bias, RMSE, NSE and MSE) as well as visual examinations. Based on the results of this study, the neural network model was found to be efficient in predicting monthly water tables at almost all the sites. The study concluded that the neural network techniques can be efficiently used for predicting water table fluctuations, particularly in data-scarce conditions

Keywords- Artificial Neural Network, Aquifer, Multilayer Perceptron, Water table fluctuations, GDM back propagation algorithm

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Introduction

Groundwater is the most important source of fresh water and constitutes a major source of water supplies for domestic, agricultural and industrial sectors in several parts of the world. Moreover, groundwater is considered to be less vulnerable than surface water sources to climate fluctuations. In recent times, Groundwater modeling is developed as a most dominant tool for optimum use & protection of groundwater and sustainable management of Ground water resource. However, since groundwater is hidden and groundwater processes exhibit a high degree of spatial as well as temporal variations which makes groundwater modeling a very difficult task. For reliable prediction, the physically based numerical model (i.e., Visual Modflow) generally requires large quantity of accurate information to assign the physical properties of aquifer domain and model parameters and to calibrate the model simulation. In practice, however, sufficient data for model development is not readily available everywhere as there is a limitation of cost and time [5, 6, and 17].

Artificial Neural Network (ANN) models are one of such models, which are treated as universal approximators and are very much suited to dynamic nonlinear system modeling [3]. The main advantage of this approach over traditional methods is that it does not require the complex nature of the fundamental process to be described in a mathematical form. After adequate training, they are able to generate suitable results for many prediction problems in hydrology [3]. This makes ANN an attractive tool for modeling groundwater fluctuations.

The artificial neural network (ANN) has been applied successfully for solving various water resource problems including time-series forecasting. [8] assessed the performance of three types of functionally different ANN models for prediction of Ground water level (GWL) fluctuations using hydro meteorological data such as past GWL, rainfall, river stage, and temperature. Coppola et al. (2003) used ANNs to build a GWL prediction model under pumping and climate conditions. A few recent studies applied ANN models to predicting the GWL in coastal aquifers. [16, 11] successfully predicted the GWL fluctuation in coastal aquifers using ANN Models with input variables such as meteorological information and GWL data. A comparative study of physical ground water model and ANN ground water model was performed by [15] as they evaluated the performance of Visual MODFLOW and ANN for simulating groundwater levels. The study revealed that ANN provides better prediction for short time steps.

Considering the problems associated with complex nonlinear process in different domains, the artificial neural networks (ANNs) have been widely used for forecasting in many areas of science and engineering in recent years [16]. Although several researchers have applied ANNs for groundwater-level prediction (e.g., [1, 2, 4, 5, 7, 12, 11, 14], however, groundwater modelling using ANN technique is a bit limited. The objective of present study was to use the ANN technique for predicting water table fluctuations at multiple sites in study area.

Study Area Description

The Hoshangabad District of Madhya Pradesh was selected as study area for current study. The study area has sufficient and authentic hydrologic and water level data at many sites which were prerequisite for the current study. The study area is bounded by Satpura mountain ranges in south and by Narmada River in the North direction. The entire study is drained by Narmada River and its tributaries. Thus, the area falls in the Narmada Basin. The River Narmada flows along the northern boundary of the district.

The study area comprising alluvial sand and gravel and/or alluvial silty sand and gravel are predominant over the region and comprise the area between the Narmada River in the North and the Satpura forest in the south [Fig-1]. All the selected sites for study were penetrating in alluvial unconfined aquifer. The hydraulic conductivity of aquifer exhibits a large spatial variability, suggesting considerable heterogeneity of the Upper Narmada basin. It varies from 65 to 804 m/day. The overall flow of groundwater in the basin is from south to north toward

Narmada River with a significant River-aquifer interaction up to a larger portion of the basin.

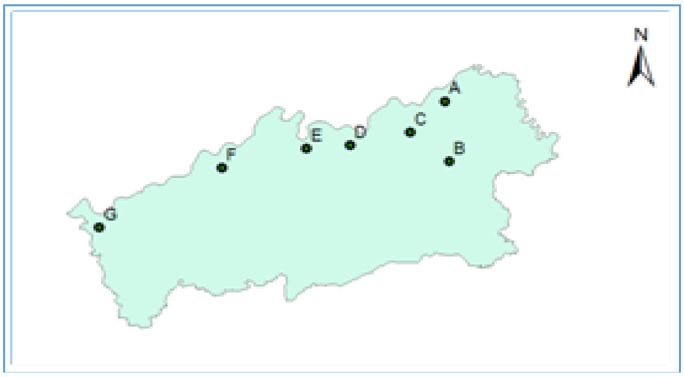

Fig-1 Map of the study area with the location of observed sites

Materials and Methods

Data Acquired

The daily rainfall data of 10 years (2005 to 2015) were received from the Geological Survey of India (GSI), State Data center, Bhopal. The daily river stage of River Narmada data were acquired from Central water commission, Bhopal. The daily maximum and minimum ambient temperature of study area were acquired from Indian metrological department, Pune. The daily water table data were obtained from Central Ground Water Board Bhopal & GSI Bhopal. The criteria used for selecting sites for this study were the long term availability of daily water table data and the continuity of data at individual sites. Based on these criteria, seven sites (A, B, C, D, E, F and G were selected for the simulation of water table fluctuations for the 2005- 2015 period by using ANN technique. The location of these sites is shown in [Fig-1] as encircled observation wells.

ANN Architectures and Training Algorithms

A neural network is inspired from the biological neuron system involving a massively parallel distributed processing system made up of extremely interconnected neural computing elements that have the ability to learn and thereby acquire knowledge and make it available for use [2]. It resembles the human brain in two aspects: (a) knowledge is acquired by the network from its environment through a learning procedure, and (b) strengths of interneuron connections, known as synaptic weights, are used to store the acquired knowledge [2].

In other words, ANN derive the relationship between a given set of inputs and desired outputs without giving any data about the actual processes involved; it is in natural learning crux based on pattern recognition. The simple unit of ANN is the neuron, which simulates the two basic purposes of natural neurons: first it calculates the weighted sum of all the inputs fed into it and this computed weighted sum is further passed by an activation function/non-linear function to generate the output. The following figure [Fig- 2] explains a nonlinear model of a neuron, which formulate the basis for designing an artificial neural network (ANN).

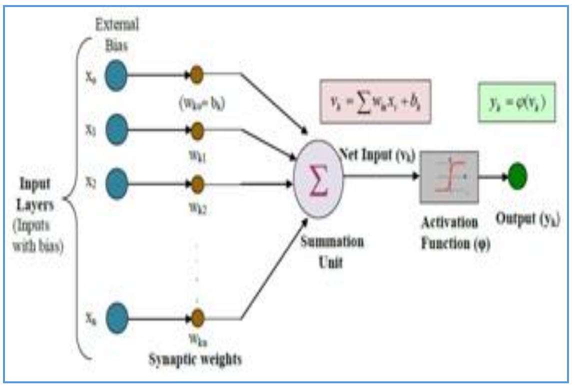

Fig-2 Basic nonlinear model of a neural network

ANN Architectures Used in the Study

In this study, Multilayer Perceptron (MLP) has been used to design ANN model for predicting monthly water tables over the study area. A multilayer feed forward network typically trained with back propagation [Fig-3] which consists of input layers, output layer(s) and one or more hidden layers. The input signal travels in only frontward direction from the input nodes to the output nodes by passing through the hidden nodes, which help in performing useful intermediate computations. The major plus point of MLP neural network is that they are quite easy to handle, and can approximate any input-output map [9].

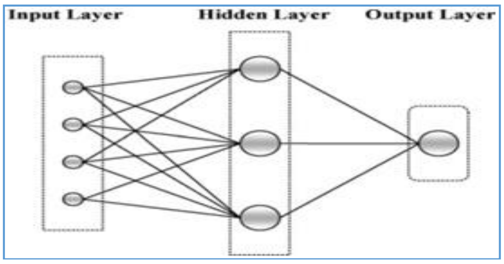

Fig-3 Multilayer perceptron.

Training Algorithm

Gradient descent with momentum back propagation algorithm was used in this study to train the ANN architecture. This algorithm uses back propagation to calculate derivatives of performance cost function with considering the weights and bias of the network. Each of the variables are attuned according to the gradient descent with momentum.

ANN Model Development

In the study, the ANN model was designed to predict water tables at seven sites [Fig-1] using a set of suitable input parameters. The parameters for the input of ANN model were decided by bearing in mind of those parameters, which have potential to affect the water table. Various steps adopted for developing ANN models are briefly described in the following sub-sections.

Inputs and ANN Parameters determination

The selection of significant input variables are one of the most imperative steps in the ANN model development process. In general, all of the relevant input variables will be equally informative some instances, because some may be noisy, correlated or have no significant relationship with the output variable being modeled [13]. In this study, monthly rainfall, ambient temperature, and mean River stage and considerable lag for 1 month & 2 month of rainfall, temperature and mean river stage of selected sites was selected for prediction of Ground water predictions. A logistic sigmoid transfer function in the hidden layer having three layers including a linear transfer function in the output layer were selected for ANN model development in this study. The monthly water table data of 7 years (2005-2012) were used for training the ANN models and those of 3 years (2013-2015) for testing. The ANN modeling was performed using the MATLAB 7.0 software.

Performance Evaluation of the Developed ANN Models

The performance evaluation of all the ANN models developed for seven sites was carried out using four statistical indicators (bias, RMSE, MAE and NSE) for training and testing periods in order to examine their effectiveness in predicting water tables at individual sites. The expressions for bias, RMSE, MAE and NSE are given by:

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$$Bias = \frac{1}{N}\sum_{i=1}^{N}\left(h_{si} - h_{oi}\right)$$

Mean Average Error:

$$MSE = \frac{\sum_{i=1}^{N}(h_{si}-h_{oi})^2}{N}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(h_{si}-h_{oi})^2}{N}}$$

Nash–Sutcliffe efficiency (NSE):

$$NSE = 1 - \frac{\sum_{i=1}^{N}(h_{oi}-h_{si})^2}{\sum_{i=1}^{N}(h_{oi}-\bar{h}_o)^2}$$

Where, hoi = mean of observed groundwater levels [L], hsi = simulated groundwater levels and N = total number of observations.

Results and Discussion

Water Table Prediction by the Developed Artificial Neural model

The developed ANN model was being evaluated for predicting water tables at seven sites. The ANN training was done using four statistical parameters *viz.*, MSE, RMSE, bias and NSE and the results are summarized in [Table-1]. The statistical parameters were determined during training period (i.e. 2005-2012) as well as testing period (i.e. 2012-2015) as shown in [Table-1]. The result suggested that ANN MLP model achieve targets quite well at sites A, B, C, D, E, F and G.

It can be visualized from [Table-1] that the NSE value ranges from 0.87 to 0.95, among all the seven sites during training & testing. The NSE vary from 0.86 (Site B) to 0.95 (Site A). Nash–Sutcliffe efficiency can vary from −∞ to 1. An efficiency of 1 (NSE = 1) corresponds to a perfect match of observed and simulated data. Similarly RMSE ranges from 0.77(Site B) to 0.95(Site C) model which indicated a reasonably good match between observed and simulated data. The values of MSE was found to be in range from 0.59 (Site G) to 0.97 (Site B) for MLP-ANN model. The low value of MSE indicated the less error while comparing observed and simulated values. It has also been found that increasing the neuron from has decreased the MSE value (i.e. increase the performance). Similarly increasing layers from 2 to 3 has also improved the predictive performance. However increasing neuron & layer above the optimum point adversely impact the performance. The values of bias calculated during the training and testing of the ANN models are negative in most of the sites (except for Site C & Site D) indicated over-prediction of water tables by the ANN model.

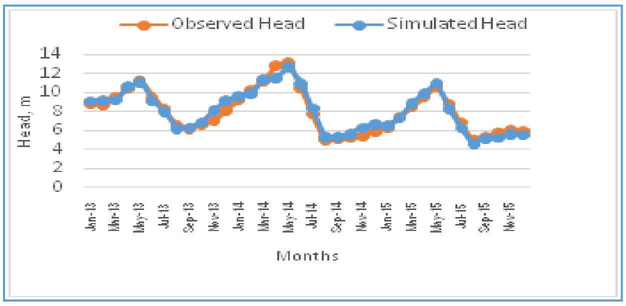

Fig-4 Observed and Simulated water heads using ANN model at Site A for the training (2013-2015) period

Table-1 *Statistical parameters measured for the ANN model at seven sites*

SITES	ANN MLP-GDM	NSE	BIAS	RMSE	MSE
A	Training	0.95	-0.08	0.8321	0.6924
	Testing	0.91	-0.12	0.8919	0.7954
B	Training	0.90	0.12	0.8919	0.7954
	Testing	0.86	0.32	0.9861	0.9723
C	Training	0.92	0.12	0.9549	0.9118
	Testing	0.95	0.07	0.8919	0.7954
D	Training	0.93	0.00	0.8919	0.7954
	Testing	0.90	-0.04	0.8415	0.7081
E	Training	0.93	0.02	0.8973	0.8051
	Testing	0.90	-0.16	0.8919	0.7954
F	Training	0.91	0.01	0.9343	0.873
	Testing	0.94	-0.26	0.8973	0.8051
G	Training	0.92	0.17	0.8919	0.7954
	Testing	0.90	-0.24	0.7692	0.5917

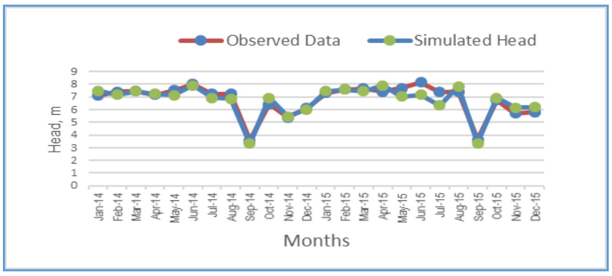

Fig-5 Observed and Simulated water heads using ANN model at Site D for the training (2013-2015) period

Conclusion

In this study, The MLP neural network architecture used for predicting monthly water table fluctuations in the study area considering relevant metrological and hydrological input variables. The effectiveness of the neural network model developed for each of the seven sites were assessed using statistical indicators as well as visual comparison of observed and predicted water tables. The ANN model was found to be efficient for predicting monthly water tables at almost all the sites. It can be concluded that neural network technique can be used successfully for the forecasting of water table fluctuations especially in the regions where the sufficiency and quality of field data are serious issues for groundwater management.

Conflict of Interest: None declared

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