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Comparison of GDM and LM Algorithms in ANN Modeling for the Estimation of Ground Water Level Fluctuations

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Abstract— **The study evaluates forecasting of groundwater level for short period of data by utilizing the standard artificial neural network (ANN) model, trained with two back propagation (BP) training algorithms namely Levenberg-Marquardt (LM) and Gradient Descent with Momentum (GDM). Data of five wells, Annual rainfall, Temperature, Relative humidity and river stage are chosen as input parameters.The model efficiency and accuracy were measured based on the root mean square error (RMSE) and regression coefficient (R).R-values approach towards the unity for most of the wells in LM method. LM method is recommended for forecasting ground water level for short duration of data and also it is anticipated that this method will give fairly accurate result for long duration of data under consideration. In case of constraint on data availability mentioned above, the LM Method is found to be suitable for ground water forecasting even when we take river water level as one of the inputs in ANN model.**

***Keywords*— ANN, LM, GDM, RMSE, R-value**

1.0 Introduction

Groundwater is the one of the major source of fresh water in many regions of the world. Groundwater is exploited to meet the domestic, irrigation and industrial demands. Hence being a precious source of water, groundwater needs an extensive and intensive monitoring for its conservation, management and forecasting. Groundwater level is one of the characteristic parameter used in forecasting problems as indicator of groundwater availability although its availability depends on groundwater flow, and the physical characteristics. The ground water table is influenced by host of factors. These factors can be grouped into metrological, geomorphological and hydrological. Uncontrolled and unaccounted demand of ground water is increasing with population which further accentuates the problem of ground water forecasting and its management. Several conceptual and physical model studies in the past, were carried out in forecasting ground water level but they were not only highly complex and time consuming but also inaccurate because of high randomness of the contributing factors and its limited availability. Physical models (Upadhyaya et al., 2001), water balance models (McCarthy et al., 1991), and statistical regression models (Yakowitz, 1976), developed in the past, need long period of ground water data to perform the modeling. Also it has been reported (Shirmohammadi et al., 2006) that observational error or uncertainties amplify the error in the output result.

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LM and GDM algorithm for ANN modeling has been used to forecast ground water level for short duration of data. Also in addition to the weather parameters, hydrological parameter of river stage has been taken as input in the model.

In recent past, artificial neural networks (ANNs) have been used in various fields of science and technology for prediction purposes (Gail et al., 2002). ANN modeling, a non-linear statistical technique, is an intelligent system which works on training algorithms with limited set of data and especially useful in non-linear time series (Hornik et. al., 1989; Guan et.al., 2004; Hill et. al.,1996; Tang et. al.,1993; Zhang.,2003;French et.al.1992). Flood and Kartem (1994 and1997) reviewed the application of ANN to various branches of civil engineering.

Earlier, ANN modeling were used in the simulation of water table fluctuations at different locations (Yang et al., 1997; Yang et al., 2000; Coulibaly et al., 2001; Coulibaly et al., 2005 Affandi et al., 2007; Banerjee et. al.,2008; Ghose et. al.,2010;Holger et.al.,2000;Nayak et. al.,2006; Rao, 2000(II)). These studies indicate that ANN modeling is a convenient tool for predicting water table fluctuation, especially in areas where the aquifer system information is not available or where the available records are relatively short.

The Present study is the continuation of these works by introducing a new hydrological parameter as one of the basic inputs in addition to weather parameters (Kumar et.al.,2009) in ANN modeling. This hydrological parameter is water level fluctuations of the river Ganges, passing through the study area. Two back propagation (BP) algorithms, used with MATLAB Programming, has been compared for the ground water level forecasting for short period of data.

2.0 Materials and Methods

The input data for the present study were collected for Kashi Vidyapeeth block, which is situated in the Varanasi City, Uttar Pradesh, India. Kashi Vidyapeeth, covering an area of 143.4 km2 lies between longitude $82^0 53'00''$ and $83^0 5'00''$ E, and latitude $25^0$13’00” and $25^0$22’00” N. Hot/dry summer and cold/dry winters characterize the area, with a distinct rainy season from June to September. The temperature ranges from 50c to 460c. Maximum rainfall in the area from last 11 year is 429mm with low average. Monthly mean water level has been collected from 5 wells fairly distributed in the area (Fig.1) during the study period 1999 to 2009. The location of wells with their latitude, longitude and RL is given in table 1. Wells are used for domestic and irrigation purposes.

The drainage system of the area is controlled by the river Ganga and its tributaries. The river Ganga flows in the east or north-eastern direction along the north-eastern and south-western boundaries of the district. Physiographically, Varanasi district lies in Alluvial plain. The plain is devoid of rocks and made up entirely of Alluvium of two types, with the newer upland. Clearly defined banks of varying heights separates the two, which marks the extreme flood limit of the river. Apart from the difference, there are local variations depending upon the slope and height. The northern alluvial plain is generally a flat land with east or north-eastward slopes on regional scale and forms a part of central Ganga plain. Varanasi is mainly underlain by Gangetic alluvium, the deposition of which commenced from the Pleistocene period after the final upheaval of the Himalayas and is still continuing. It consists of inter-bedded layers of sand, silt and clay. The surface water bodies are rivers and streams, lakes, springs, ponds and tanks etc.Drainage pattern of the area is well defined by Fig. 2 in which different types of drainage are observed in the unutilized area.

3.0 Feed Forward Neural Network (FFNN)

Artificial neural networks (ANNs) are information processing which simulate the present understanding of the biological nervous systems (Mc Culloch et. al., 1943). The processing units, called neurons of an ANN are arranged in layers and are connected by links of variable strengths called weights. Most units in neural networks transform their net input by using a function called an "activation function" (Rao, S.,2000(I)). Activation function, sometimes called transfer or squashing function, yield a value called the unit's "activation". This activation value is fed to one or more other units. Activation functions for the hidden units are needed to introduce

FIG 1: MAP OF KASHI VIDYAPEETH BLOCK

TABLE 1: THE LOCATION OF THE WELLS WITH THEIR LATITUDE, LONGITUDE AND RL

Well no.	Location	Latitude	Longitude	R.L of GL (m)
1	Lanka	$25^0$16’55”	$83^0$00’40”	77.45
2	Bhatti	$25^0$17’00”	$82^0$55’05”	80.28
3	Tikari	$25^0$14’00”	$82^0$59’00”	80.58
4	Kashi Vidyapeeth	$25^0$19’00”	$82^0$59’00”	78.5
5	Cantt	$25^0$21’00”	$82^0$59’40”	80.76

nonlinearity into the network. For the output units, an activation function should be chosen to suit the distribution of the target values.

Recently, feed forward neural network (FFNN) modeling technique in ANN has been used increasingly to predict groundwater level fluctuations. The FFNN has one input layer with one or more hidden layers. In the feed forward neural network, signals are transmitted in one direction, only from inputs to outputs. In standard feed forward architecture, layers of nodes are connected between one layer to the subsequent layers. The hidden layers are placed between set of input nodes called, input layer and the set of output nodes called, output layer. Information fed to input layer is processed by weight and passed to the next layer. The numbers of neurons in the input layer and the output layer are determined by the numbers of input and output parameters, respectively. The model is shown in Figure 3 where i, j, k denote nodes input layer, hidden layer and output layer, respectively.wij is the weight of the connection between i and j nodes. Commonly, neural network modeling follows three steps: database collection; analysis and preprocessing of the data; training of the neural network. The latter includes the choice of architecture, training functions, training algorithms and parameters of the network; testing of the trained network; and using the trained neural network for simulation and prediction.

4.0 The Back propagation Algorithm

Backpropagation is a training procedure for feed-forward

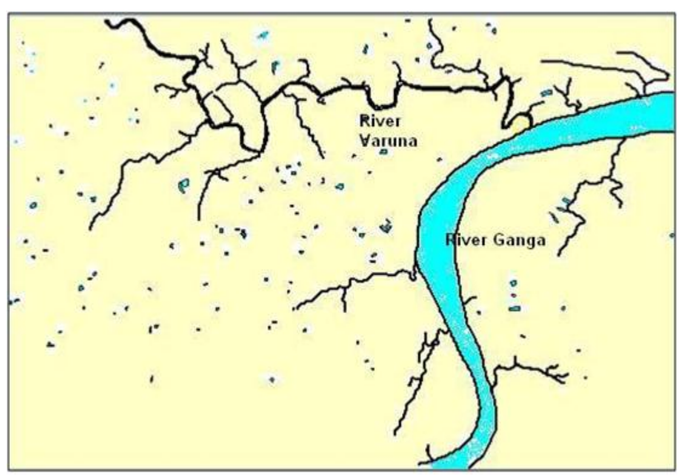

FIG 2. DRAINAGE AND WATER BODIES OF STUDY AREA

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neural networks that consists in an iterative optimization of a so called error function representing a measure of the performance of the network. During the training process a set of pattern examples is used, each example consisting of a pair with the input and corresponding target output. In an iterative manner the appropriate weight corrections are performed during the process to adapt the network to the desired behavior. Each iteration of the algorithm is composed of a sequence of three steps (Haykin, 2006):(i) Feed a pattern example to the input layer of the network and make it to propagate sequentially through all the neuron layers until a result is obtained at the output units. The activation value of a unit in any layer is calculated using a sigmoid activation function; (ii) The generalized delta rule (GDR) is used to calculate the values of "weight update" defined at given time step;(iii)Finally, the weights are updated. A momentum term in the BP algorithm is used to incorporate some influence of the past iterations in the present weight update. It has been shown that, in general, it improves the convergence of the BP algorithm. Furthermore, it is possible that it allows a range of different learning rate values to produce approximately analogous convergence times.

Two BP algorithms namely, Levenberg-Marquardt (LM) and Gradient Descent with Momentum (GDM), has been used and compared for the ground water level forecasting for short period of data.

4.1 Levenberg-Marquardt (LM)

The Levenberg-Marquardt algorithm uses the following Newton-like update

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \qquad (1)$$

where J is the Jacobean matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobean matrix can be computed through a standard back propagation technique. When the scalar μ is zero, this is just Newton's method. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

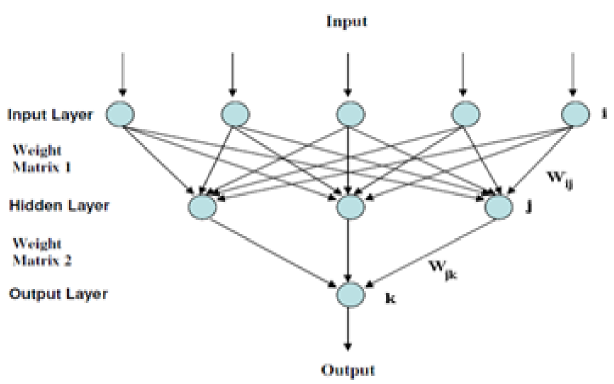

FIG.3. A TYPICAL THREE-LAYER FEED FORWARD ANN

4.2 Gradient Descent with Momentum (GDM)

GDM can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance (p) with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent with momentum,

$$dX_{k+1} = m_c \times dX_k + lr \times (1 - m_c) \times dp/dX \qquad (2)$$

Where dX_k **is** the previous change to the weight or bias, $\mathbf{l_r}$ is learning rate, $\mathbf{m_c}$ is momentum constant. Mean absolute error performance is **dP/dX**. Training stops when any of the following conditions occurs: the maximum number of epochs is reached the maximum amount of time is exceeded performance is minimized to the goal or the performance gradient falls below minimum gradient.

5.0 Performance Measures

The efficiency/response of the selected network (in different sets) for accurate output is measured using statistical indices, viz. root mean square error (RMSE) and correlation coefficient(R).

(i) Root Mean Square Error (RMSE)

Root mean square error defines the overall error of the estimated value. Less root mean square error means accuracy of the value is high.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(O_i - P_i)^2}{N}}$$

Where $\mathbf{O_i}$ and $\mathbf{P_i}$ are respectively actual and estimated value of the $\mathbf{i^{th}}$ data.

(ii) Correlation Coefficient(R)

R is the square of the correlation between the response values and the predicted values. It defines the relation of the actual and estimated value.

$$R = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}}$$

Where $\bar{O}$ and $\bar{P}$ are respectively mean of actual and estimated values.

6.0 Inputs and Output of the Network

Five input parameter is used for years 2000 to 2009 (Table.2). In each of year, only January, March, May, June, October and December data is used. Weather data (2000-2009) of Humidity, Rainfall and Temperature are taken from Indian Metrological Department (IMD), B.H.U Varanasi. Ground water level data of five wells are taken from State Ground Water Board, Varanasi and River Ganga water levels of are taken from Central Water Commission. Out of the 10 years of historic monthly groundwater level,1 to 8 years of data has been used to train the neural network. The remaining 2 years of groundwater level data has been used to validate the efficiency of the ANN model through performance measures used in this study.

7.0 Results

7.1 LM Method

ANN configuration and performance measures for LM method is given in the table 3.
Trend of actual and predicted values for each of the five wells is shown in the figure 4.

7.2 GDM Method

ANN configuration and performance measures for GDM method is given in the table 4
Trend of actual and predicted values for each of the five wells is shown in the figure 5.

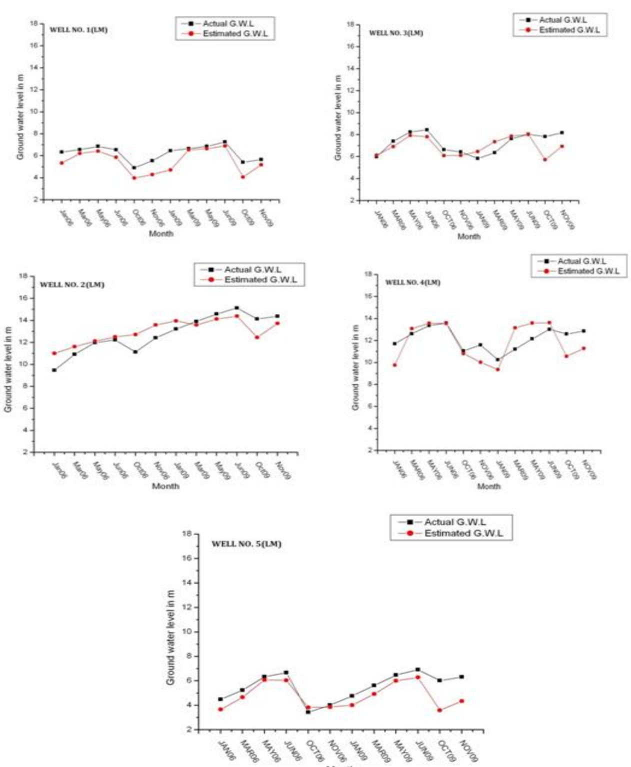

FIG.4. ACTUAL AND ESTIMATED GROUND WATER LEVELS FOR LM METHOD.

Table 2: ANN INPUTS AND OUTPUT OF THE NETWORK

Inputs	Output
1. Humidity (%)	
2. Rainfall (mm)	Ground water Level
3. Minimum Temperature (oc)	
4.Maximum Temperature (oc)	
5.River Water Level	

8.0 Conclusion

Comparison in terms of absolute error in GWL shows that most of the values obtained by GDM method is on higher side than values obtained by LM method. R-values in LM method is not only more than R-values in GDM method but also approach to unity in most of the wells (well no. 1, 2, 3). Thus at first it seems that GDM shows closer resemblance of observed and calculated GWL values but RMSE values in both the methods does not provide any relative merit of both methods. Lack of anticipated performance can be attributed to the unavailability of sufficient historical data. Therefore LM method provides a reliable forecasting of ground water fluctuations when river water level fluctuation in river, passing through the study area, is taken as one of the input in ANN modeling for short duration of data.

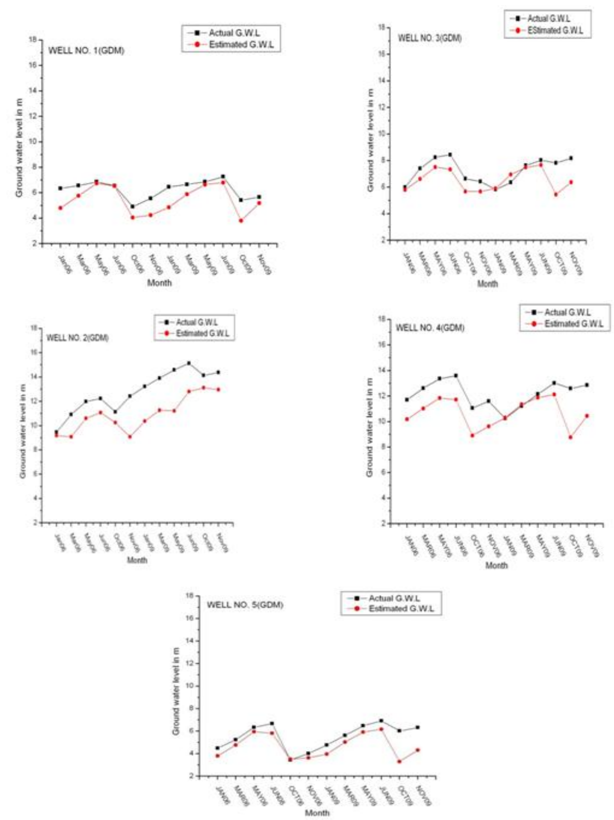

FIG.5. ACTUAL AND ESTIMATED GROUND WATER LEVELS FOR GDM METHOD

Table3: ANN CONFIGURATION AND PERFORMANCE MEASURE FOR LM METHOD

Well No.	LM Method							
	No. of Layers	No. of Neurons	R		RMSE		Abs.Error in GWL	
			Training	Testing	Training	Testing	Max.	Min.
1	2	4	0.691	0.909	1.15	0.889	1.74	0.2
2	2	4	0.738	0.846	2.379	0.984	1.67	0.13
3	2	4	0.785	0.931	1.354	0.843	2.11	0.01
4	2	4	0.668	0.641	3.463	1.294	2.03	0.04
5	2	4	0.794	0.787	1.236	1.043	2.42	0.16

Table4: ANN CONFIGURATION AND PERFORMANCE MEASURE FOR GDM METHOD

Well No.	GDM Method							
	No. of Layers	No. of Neurons	R		RMSE		Error in GWL	
			Training	Testing	Training	Testing	Max.	Min.
1	2	4	0.581	0.845	1.139	0.981	1.61	0.01
2	2	4	0.563	0.810	3.351	2.106	3.33	0.29
3	2	4	0.634	0.589	1.268	1.054	2.38	0.07
4	2	4	0.549	0.473	2.984	1.834	3.83	0.05
5	2	4	0.667	0.542	1.181	1.118	2.72	0.06

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