Neural Network Model for Prediction of Ground Water Level in Metropolitan Considering Rainfall-Runoff as a Parameter

Sanjeev Kumar, Ajay Indian, Zubair Khan

Abstract -- In metropolitan area the ground water is the important resource of drinking water. To preserve the ground water level several rain water harvesting techniques are implemented now a days. A neural network model has been developed for ground water level prediction. Various models developed before for ground water level prediction with artificial neural network methodology. Most of these models these models consider rainfall and current ground water level as input parameter. This model considers rainfall-runoff as an important factor which represents the performance of rain water harvesting techniques in urban area. So this model predicts the ground water level with the effect of rain water harvesting techniques.

Index Terms --Artificial neural network, ground water level, rainfall-runoff, backpropogation feed forward network, Levenberg-marquardt algorithms.

I. INTRODUCTION

Drinking water in any metropolitan area is entirely governed by ground water. The consumption of water increases everyday with the growth in population. The ground water level is going down day by day. To preserve ground water level rainfall plays vital role. But due to civilization complete utilization of rainfall is almost impossible in any developed city. So for complete utilization of rainfall, rain water harvesting plants are implemented. For management of ground water level a model is required which can predict the ground water level in future with the current available information. This model must include the parameter which shows the effect of rain water harvesting plants. So that with the change of number of rain water harvesting plants the ground water level can preserve. Artificial neural network provides bestmodel for prediction. To achieve the greater efficiency and accuracy a neural network model is developed in this paper for prediction of ground water level.

II. ARTIFICIAL NEURAL NETWORK

Artificial neural network is a biologically inspiredmathematical tool used widely for prediction andclassification. In basic Artificial neural network there are three layers of artificial neurons given below

1) Input layer: The function of this layer is to take input.
2) Hidden layer: This layer process that input as per the given activation function.
3) Output layer: After processing by hidden layer output layer provides the output.

Manuscript Received on July, 2013

Sanjeev Kumar, M.Tech (Research Scholar), Department of Computer Science and Engineering, Invertis University, Bareilly, India.

Ajay Indian, Department of Computer Application, Invertis University, Bareilly, India.

Zubair Khan, Department of Computer Science and Engineering, Invertis University, Bareilly, India.

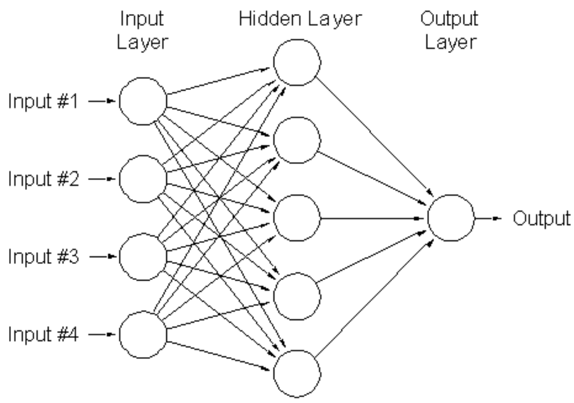

Fig 1.1 Artificial neural network

An Artificial neuron is a processing unit which process the input. The input is taken by an input vector x. Each edge connecting two neurons has some weight Wij shows the connection strength between two neurons. The weights are given in weight matrix W. Each neuron has some activation function or some transfer function given as

$$Y = \phi\,(I)$$
$$I = \sum w_{ij} \quad x_i \;-\theta_i$$

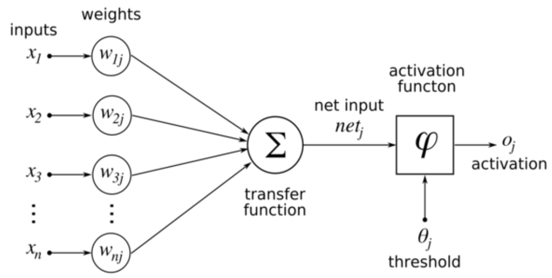

Fig 1.2 Artificial Neuron

III. RELATED WORK

Amutha R et. al. [1] uses two neural network model ANFIS and RBF for prediction with 25 years of data. M. Kavita and K.B. Naidu [2] use ANN and ANFIS but also MFIS and compare the performance of each. Srinivasulu D and Deka P.C. [3]work on RBF and FFBN and compare that. Other than these P.sujata and G.N. Pradeep [4] compare 4 types of ANN the two are common feed forward network and RBF and another two are Elman Type Recurrent Neural Network and Input delay Neural Network with P Memory order. In all these research work ANFIS, RBF,FFBN and FF with Levenberg-Marquardt training algorithm are common networks while Elman type recurrent network and Input delay NN with p memory order are the network which used very rarely.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The feedforward neural network with Levenberg-Marquardt training algorithm provides better prediction values than any other network.

IV. PARAMETER USED FOR PREDICTING GROUND WATER LEVEL

Input parameters for neural network model are decided on the basis of their effectiveness. The first parameter is the rainfall which plays an important role inpreserving the ground water level. Next parameter is the current ground waterlevel on the basis of that prediction has been done. The next parameter is rainfall-runoff, which includes the effect of rain water harvesting plants. It represents the utilization of rainfall. So it becomes an important consideration.

V. METHODOLOGY

A. Feed forward neural network Architecture.

Feed forward neural network have been applied successfully in many different problems since advent of the error backpropogation learning algorithm. This network architecture and the corresponding learning algorithms can be viewed as a generalization of the popular least-mean-square(LMS) algorithms.

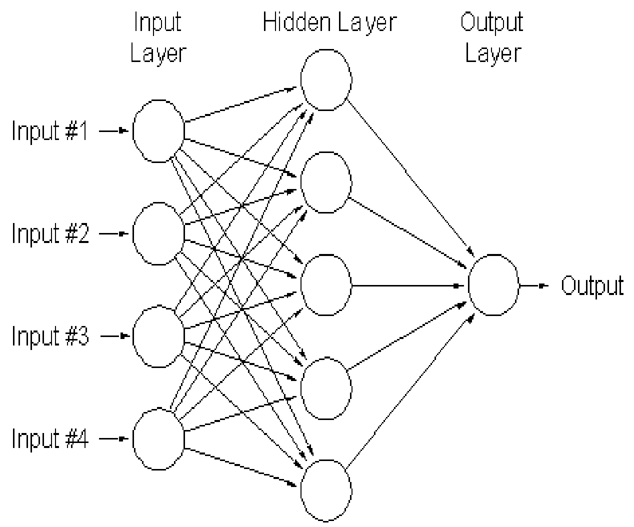

Fig 2.1 Feed Forward Neural Network

A multilayer perceptron network consists of an input layer, one or more hidden layers of computation nodes, and an output layer. Fig 2.1 shows a typical feed forward network with one hidden layer consisting of three nodes, four input neurons and one output. The input signal propagates through the network in an forward direction, layer by layer. Their main advantage is that they are easy to handle and can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data.

B. Levenberg-Marquardt Training algorithm.

The Levenberg-marquardt method is a modification of the classic Newton algorithm for finding an optimum solution to a minimization problem. The update rule of the Gauss-Newton algorithm is presented as

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

In order to make sure that the approximated Hessian matrix $J^T J$ is invertible, Levenberg-Marquardt algorithm introduces another approximation to Hessian matrix:

$$H = J^T J + \mu I \qquad (2)$$

It uses and approximation to the Hessian matrix in the following Newton-like weight update

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e (3)$$

Where x the weights of neural network, J the Jacobian matrix of the performance criteria to be minimized, µ a scalar that controls the learning process and e the residual error vector.

When the scalar µ is zero, Eq. (1) is just the Newton's method, using the approximate Hessian matrix. When µ is large, Eq. (1) 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 towards Newton's method as quickly as possible.

Levenberg-Marquardt has great computational and memory requirements and thus it can only be used in small networks. The Levenberg-Marquardt algorithm is often characterized as more stable and efficient.

VI. PERFORMANCE EVALUATION CRITERIA.

Two criteria are used to evaluate the performance of the neural network prediction model and its ability to make precise prediction. The mean square error calculated as:

$$MSE = \frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n} \qquad (4)$$

And correlation coefficient R^2

$$R^2 = 1 - \frac{\sum (x_i - y_i)^2}{\sum x_i^2 - \frac{\sum y_i^2}{n}} \qquad (5)$$

Where, x_i= observed ground water levels, x = mean of x_i , y_i= predicted ground water levels, y = mean of y_i and n = the number of data set used for evaluation. The best fit between observed and calculated values, which is unlikely to occur, would have MSE=0 and R^2 =1.

VII. STUDY AREA AND DATA.

In this research area chosen must be fully developed metropolitan area. So Delhi is selected for this research. Delhi is located at 28.61°N 77.23°E, and lies in Northern India. Delhi is a metropolitan region in India that includes the national capital city, New Delhi. The National Capital Territory of Delhi covers an area of 1,484 km^2 (573 sq. mi). It is India's second-most-populous city after Mumbai, and the largest city in terms of area. With a population of 22 million in 2011, the city is the fourth-largest city in the world. Temperatures in Delhi range from -2.2 to 48.5 °C (28 to 119.3 °F). The annual mean temperature is 25 °C (77 °F); monthly mean temperatures range from 13 to 32 °C (55 to 90 °F). The highest temperature recorded in July was 45°C (113 °F) in 1931. The average annual rainfall is approximately 714 mm (28.1 in), most of which falls during the monsoon in July and August. The average date of the advent of monsoon winds in Delhi is 29 June. In Delhi a huge number of rain harvesting plants are implemented.

Fig3.1 Map of Delhi

Three input parameters are taken for the neural network input given as ground water level, rainfall and rainfall-runoff. The ground water level data is taken from 53 wells placed in various parts of Delhi. The time period for this work is of 5 years from 2005 to 2010.The readings are taken quarterly. The values are taken from the government's official websites. Missing data values and other errors are resolved with standard techniques of data preprocessing.

VIII. RESULT AND DISCUSSION

After deciding the inputs (Ground water level, rainfall, and rainfall-runoff) and the neural network model (3 input nodes, 20 hidden node and 1 output node) the data fed into the Matlab 2010a environment with Feed Forward network. The training is done with Levenberg-marquardt back propagation algorithm. 977 samples are used for simulation, which divided by tool in 3 parts, training 683samples, validation 147 samples and testing 147 samples.The results are as:

	Sample	MSE	R
Training	683	3.24359e-6	.996055
Validation	147	4.19535e-6	.994619
Testing	147	5.30469e-6	.994271

The performance is checked by Mean Square Error and graph shows that the performance is much better in present work. The other performance criterion is regression coefficient and the higher values show a great relation in between variables.

After successfully developing neural network model a data of 30 samples fed into this model and the results are given as: Mean Square Error

MSE= 1.95216e-6

And Regression Coefficient

R=8.55740e-1

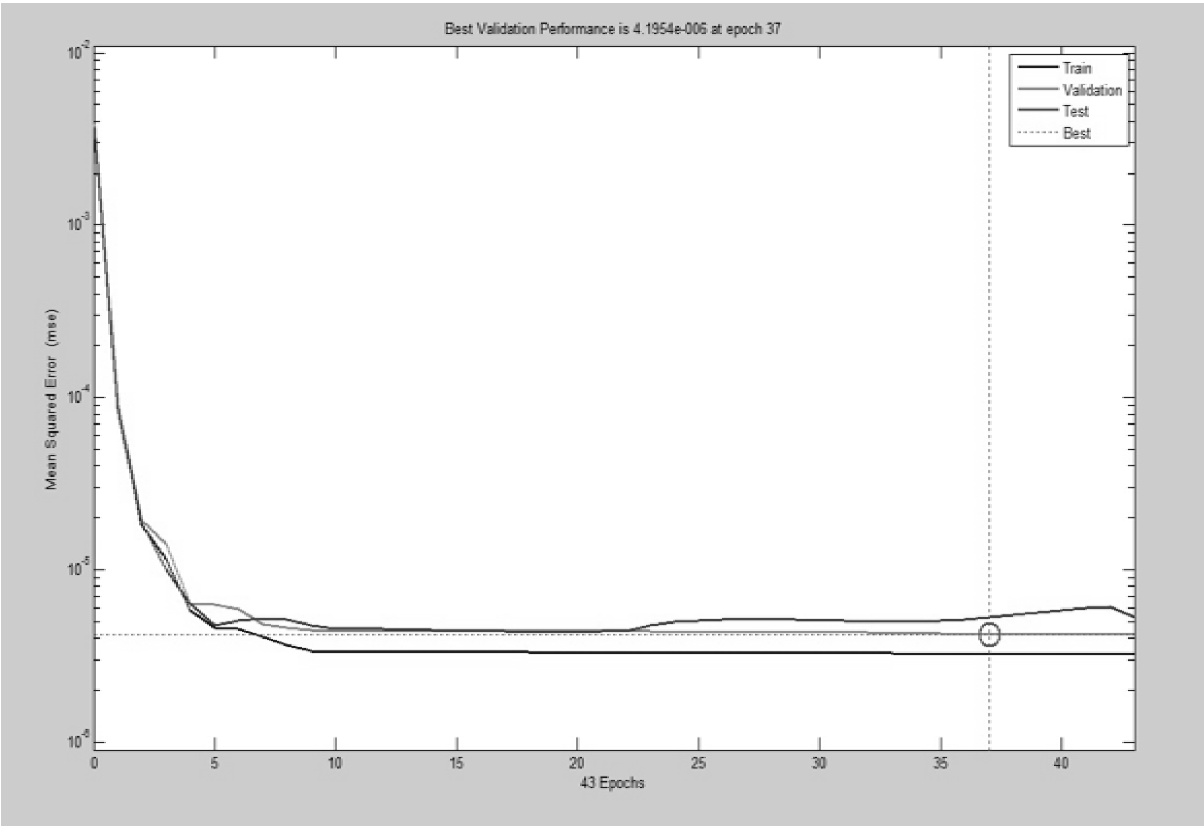

Fig4.1 Mean Square Error Graph.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

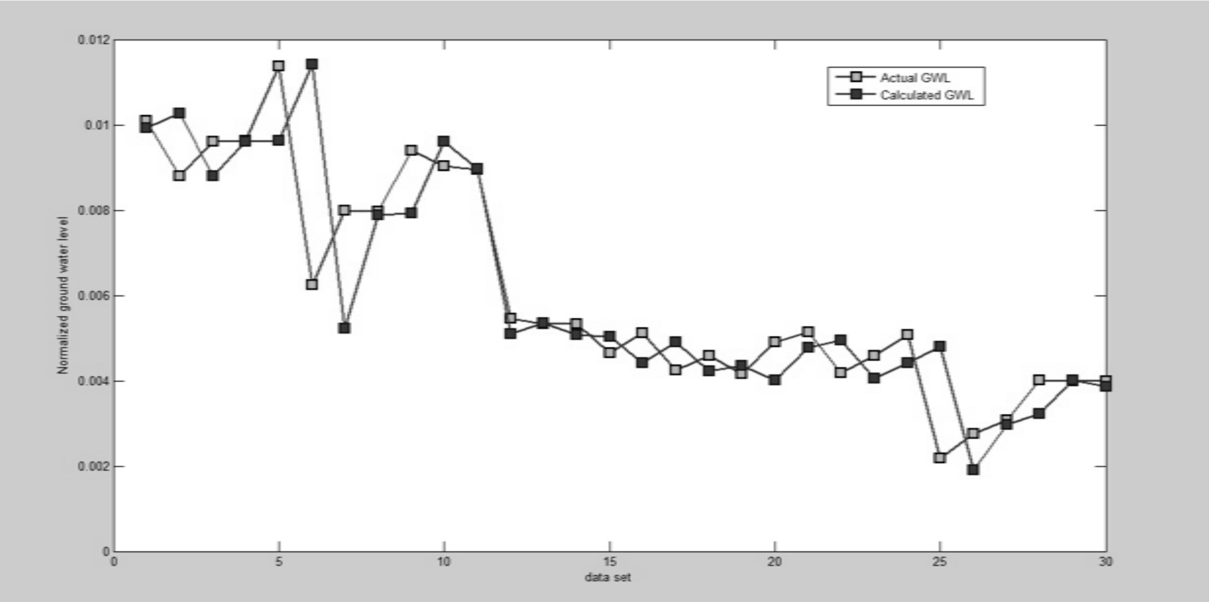

Fig 4.2 Comparison between Actual GWL and Calculated GWL

This observation suggest that Feed Forward network trained with training algorithm ‘Levenberg-Marquardt’ is efficient in prediction the ground water levels with data of a metropolitan region in very short period.

IX. CONCLUSION AND FUTURE WORK.

In cities like Delhi where vast area depends largely on ground water resources, non-availability of groundwater level records for sufficient period has been the main hindrance in developing a model for prediction of realistic ground water levels. Without considering the rainfall-runoff it is very difficult to predict ground water level in future. In this work an attempt was made for more accurate prediction of groundwater levels with the data of shorter period for the observation wells located in Delhi (India). Feed forward network trained with training algorithm ‘Levenberg-Marquardt’ and found very effective to predict the ground water levels quarterly.

In future work some other models can be used for groundwater level prediction. As the prediction of ground water level is a time-series problem, various other tools could show better results. For example NARX is a time series tool which is showing its efficiency in other time series problems and can be used in ground water level prediction.

REFERENCES

1. Amutha R. and Porchelvan P. “Seasonal prediction of groundwater levels using anfis and radial basis neural network*”, International Journal of Geology, Earth and Environmental Sciences*, 2011 Vol. 1 (1) September-December, pp.98-108.
2. M.KavithaMayilvaganan , K.B.Naidu “Application of Soft computing techniques for Groundwater Level Forecasting”,*2012 International Conference on Computer Networks and Communication Systems* (CNCS 2012),IPCSIT vol.35(2012) © (2012) IACSIT Press, Singapore.
3. Sreenivasulu D and Deka P.C “Groundwater Level Forecasting using Radial Basis Function with Limited Data*”, International Journal of Earth Sciences and Engineering*, ISSN 0974-5904, Volume 04, No 06 SPL, October 2011, pp. 1064-1067.
4. P. Sujata and G. N. Pradeep “Prediction of groundwater levels using different artificial neural network architectures and algorithms”, *ICA2757*, 18-May-2011.
5. Ioannis N. Daliakopoulos, Paulin Coulibaly, Ioannis K. Tsanis “Groundwater Level Forecasting Using Artificial Neural Network”, *Journal of Hydrology*, 309(2005), pp 229-240.
6. P. D. Sreekanth, N. Geethanjali, P. D. Sreedevi, Shakeel Ahmed, N. Ravi Kumar and P. D. Kamala Jayanthi “Forecasting groundwater level using artificial neural networks” , *Current science*, vol. 96, no. 7, 10 april 2009.
7. V. Nourani, A. Hosseini Baghanam, F. DaneshvarVousoughi, M.T. Alami “Classification of groundwater level data using som to develop ann-based forecasting model” , *International Journal of Soft Computing and Engineering (IJSCE)*, ISSN: 2231-2307, Volume-2, Issue-1, March 2012.
8. Heesung Yoon, Seong-Chun Jun, Yunjung Hyun , Gwang-Ok Bae, Kang-Kun Lee, “A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer”, *Journal of Hydrology* 396 (2011),pp 128–138.
9. Faridah Othman and Mahdi Naseri “Reservoir inflow forecasting using artificial neural network*”, International Journal of the Physical Sciences* Vol. 6(3), pp. 434-440, 4 February, 2011.
10. Purna C. Nayak,Y.R. Satyaji Rao and K. P. Sudheer “Groundwater Level Forecasting in a Shallow Aquifer Using Artificial Neural Network Approach”, *Water Resources Management* (2006) 20: pp 77–90.
11. Martin T. Hagan and Mohammad B. Menhaj “Training Feedforward Networks with the Marquardt Algorithm*”, IEEE Transactions on Neural Networks*, Vol. 5, No.6, pp 989-993, November 1994
12. www.rainwaterharvesting.org, 5 June, 2013
13. http://www.imd.gov.in/section/hydro/distrainfall/webrain/delhi/delhi.txt, 3 June, 2013
14. http://gis2.nic.in/cgwb/ , 9 June, 2013

AUTHORS PROFILE

Sanjeev Kumar is Research Scholar at Invertis University, Bareilly, India, pursuing M.Tech. in computer science and Engineering. He has completed M.C.A. degree from Uttar Pradesh Technical University. His research interest includes Artificial Neural Network, Data mining and Theory of Computation.

Ajay Indian is Associate Professor at Invertis University, Bareilly, India. He is head of department of Computer Applications at Invertis University. His research interest includes Data Mining, Artificial Intelligence, Handwritten character recognition and others.

Zubair Khan is Associate Professor at Invertis University, Bareilly, India. He is head of department of Computer Science and Engineering at Invertis University. His research interest includes Parallel Computing, Soft Computing, Data Mining, load balancing in multiprocessor architecture and Theory of Computation.