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Performance of Artificial Neural Network Models for Groundwater Level Forecasting in Dhaka City

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Abstract: *The groundwater levels beneath Dhaka have been experiencing a sharp decline in the recent decades due to over extraction of groundwater to meet the growing demands of the booming population. Where conditions like this prevail, it is of prime importance that the authorities in charge of groundwater management be able to properly forecast the future positions of the groundwater levels, which may help them in taking important decisions. In this study, four different feed-forward artificial neural network (ANN) models with the training algorithm of Levenberg-Marquardt have been developed to forecast groundwater levels of three areas within Dhaka city with a lead time of one month. All the groundwater extraction within the study areas occur from the same underlying aquifer beneath the city. While three ANN models predict the groundwater levels of three separate areas individually and another model predicts the groundwater levels of all three areas in a combined manner. The relative efficiencies and performance of the four models were compared using various statistical indices. The results indicate that the models which forecast the groundwater levels of single area at a time yield relatively better than a model that forecast the levels of multiple areas simultaneously.*

Keywords: *Dhaka, Groundwater Level Forecasting, Artificial Neural Network, Levenberg-Marquardt.*

Introduction

Groundwater, much like many other natural resources, is being globally overexploited at an increasing rate. Its popularity all over the world comes from the fact that it has a less probability of being contaminated than other surface water sources, it is readily available and with the advent of newer and cheaper technologies, it is easily extractable. Since many localities are becoming dependent on groundwater to meet their increasing water requirements, aquifers containing groundwater are drying up in many places as they are not getting enough time to naturally recharge themselves.

Some of the negative aspects of continuous depletion of groundwater levels are decreasing well yields, increasing pumping costs, deterioration of water quality, damaging of aquatic ecosystems, intrusion of saline water into sweet water aquifers and land subsidence. Global groundwater depletion is even being considered

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appreciable enough to contribute to a rise in sea levels due to pumped water from wells ending up in the sea, be it by runoff, evapotranspiration or precipitation (Sahagian et al, 1994). Even after being aware of the damaging effects of overexploitation of groundwater, it has become difficult to stop doing so as the use of groundwater has become important in meeting the demands of rapidly expanding urban, industrial and agricultural water requirements of today's society.

Dhaka city is facing an unplanned expansion of 3.5 percent every year (Islam et al, 2010), the population has reached a number of more than seven million (BBS, 2009) and 25 percent of this population lacks direct access to potable water (Nishat et al, 2008). To meet this massive water demand, groundwater is being extracted at a very high rate and in an unplanned manner, causing the groundwater table to deplete 20 to 30 meters in the past three decades (Zahid et al, 2004) and currently it continues to sink 3.5 meters per year in the main part of the city (DWASA & IWM, 2008) The reason why the city is dependent on its groundwater reserves is because the large rivers nearest to it are heavily polluted due to indiscriminate discharge of domestic waste water and industrial effluent, thus making the treatment of surface water a big challenge. Dhaka Water Supply and Sewerage Authority (DWASA), the authority responsible for providing water to the city, produces almost 2110 million liters of water per day, of which 87 percent is from groundwater abstraction by DWASA's 605 deep tube wells and the remaining 13 percent is from surface water treatments. (DWASA, 2012) All of this has created an extensive cone of depression in the southern-middle part of the City (Hoque, 2004). The steep piezometric gradient close to the rivers indicate contamination of the aquifer by leakage induced recharge from the rivers (Darling et al, 2002). Also, a recent study shows that land subsidence in Dhaka city will be 6.4 cm from 2000 to 2020 (DWASA & IWM, 2008). Thus, it has become essential to study the groundwater table fluctuations for proper planning, development and management of groundwater resources. This is where the role of artificial neural network (ANN) steps in.

An ANN is an information-processing construct that consists of a number of interconnected processing elements called nodes, analogous to neurons in the brain. Each node combines a number of inputs and produces an output, which is then transmitted to many different locations, including other nodes. ANNs are massively parallel computational models consisting of densely interconnected adaptive processing units. ANNs have been used in many science and engineering fields including hydrology as they are effective in modeling virtually any nonlinear function to an arbitrary degree of accuracy where the underlying complex physical relationships between the inputs are not clear. Other than time series forecasting, which has been done in this study, they are also effective in pattern recognition and process control. One of the most important advantages of ANN models is their ability to adapt to recurrent changes and detect patterns in a complex natural system.

Some earlier works on groundwater problems using ANN are forecasting the groundwater level using rainfall, temperature, and stream discharge as inputs (Daliakopoulos et al, 2005), evaluating the groundwater level in fractured media (Lallahema et al, 2005) and using of ANN to forecast groundwater levels in a shallow aquifer (Nayak et al, 2006).

Methodology

Study Area

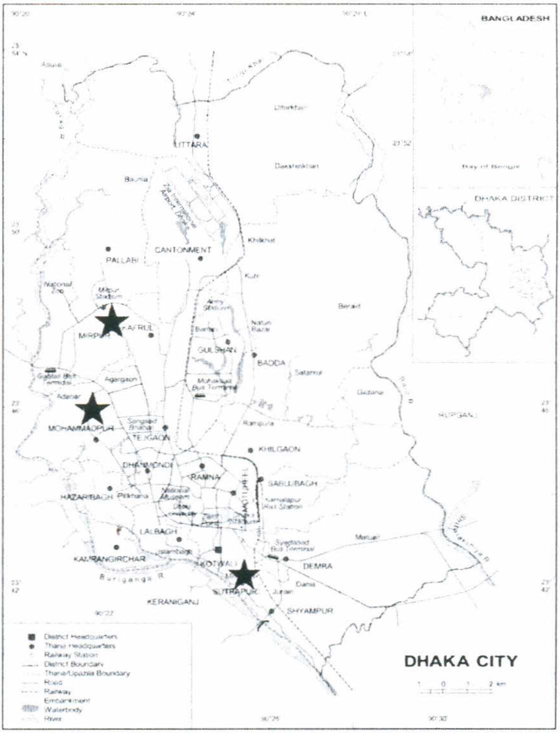

Figure 1: Map of study area with locations of selected observation wells marked by stars (from top to bottom: Mirpur, Mohammadpur, Sutrapur)

Dhaka city is located between 23°40"N and 23°54"N latitude and 90°20"E and 90°31"E longitude covering an area of about 300 km^2. The average altitude of Dhaka city is between 6.5 to 9 m above the mean sea level. The principal aquifer beneath Dhaka is formed by the Pliocene multilayer Dupi Tila formation and it is effectively confined by the semi-pervious Madhupur clay formation. The aquifer can be separated into three units based on grain-size distribution of the aquifer materials and hydraulic properties, the upper Dupi Tila aquifer-1, upper Dupi Tila aquifer-2 and lower Dupi Tila aquifer (DWASA & IWM, 2008). The Dupi Tila aquifer occurs at a depth of 8 to over 45 m below ground surface. The thickness of the aquifer varies from 100 m to over 350 m with an average thickness of about 140 m.

The aquifer is in direct hydraulic connection with the Buriganga river and other regional streams. The recharge to the Dupi Tila aquifer is by topographically driven vertical leakage through the Madhupur clay, as observed at an equivalent occurrence of the Dupi Tila aquifer, on the Barind Tract in north-west Bangladesh (Ahmed, 1994).

Three groundwater monitoring wells within Dhaka city has been selected for this study, which are operated and maintained by the Bangladesh Water Development Board (BWDB). The wells are located in Mirpur, Mohammadpur and Sutrapur (Figure 1). These three observation wells draw ground water from the same aquifer and that's why all the input data of the three locations has been correlated for the study.

Data Collection

Weekly time series records of these wells has been collected from BWDB along with daily surface water levels of the rivers Buriganga, Balu and Turag. Daily maximum, minimum and average temperatures, humidity and rainfall data of Dhaka city has been collected from Bangladesh Meteorological Department. Finally, the total annual groundwater abstraction data of pumps operated by DWASA was collected from the authority. All of the abovementioned collected data was of the time frame between 1990 and 2012, and they has been converted into a monthly format before using them as inputs in the ANN models.

ANN Modeling

A flow chart mentioning the general steps of creating and using an ANN model for groundwater level forecasting of the study area is given in Figure 2.

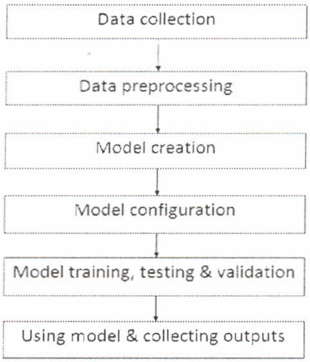

Figure 2: General steps for creating and using an ANN model

A feed-forward neural network has been selected for this study, which is a very common type of ANN. The difference between the various types of ANNs modeling approach is to arrange the nodes (architecture) and the ways to determine the weights and functions for training the network. A feed-forward neural network consists of an input layer, which is connected to one or more hidden layers, which are then finally connected to an output layer. Figure 3 shows a typical feed-forward network having one hidden layer with several nodes and an input layer and an output layer.

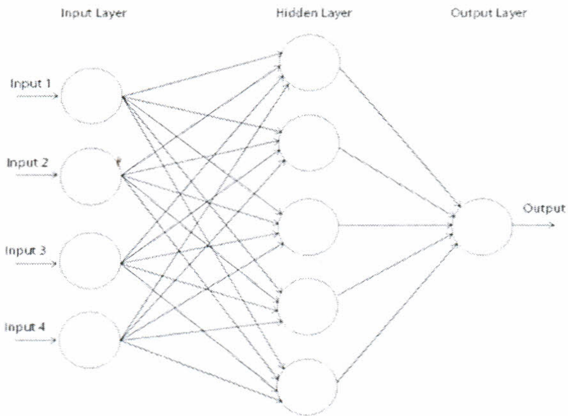

Figure 3: A typical feed-forward neural network

Twelve different input variables or dataset has been used in each of the ANN models. Three ANN models have been developed in the study consisting of one output nodes which represent the groundwater levels of successive months of input data for the corresponding study area. These three single-output models have been referred to as the individual models henceforth. Another ANN model has been developed consisting of three output nodes in its output layer, representing the groundwater levels of all three study areas for the consecutive months of the input data. This one has been referred to as the combined model in the remaining sections of this paper. The three individual ANN models presenting the output of Mirpur, Mohammadpur and Sutrapur areas have been termed as Model-1, Model-2 and Model-3 respectively and combined model has been termed as Model-4 later on.

The Levenberg-Marquardt(LM) algorithm has been chosen for this study as the backpropagation algorithm. LM algorithm is one of the fastest, more stable and efficient methods for training feed-forward neural networks. The backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer networks. Transfer functions or activation functions need to be selected for the layers of ANN, which in this study was the tan-sigmoid transfer function for the hidden layer and linear function for the output layer. Also, for modeling ANN networks, the general practice is to first divide the input data into three subsets for training, validation and testing respectively. All available input dataset of this study has been divided with the ratio of 70:15:15 for training, validation and testing respectively and data division has been done randomly.

To evaluate the performance and error of the models to be studied, the following statistical indices has been used: determination coefficient (R^2), maximum absolute error (MAE), maximum relative error (MRE) and root mean squared error (RMSE). The value of R^2 is 1 for perfect correlation and zero for no correlation at all, while the values of MAE, MRE and RMSE will be zero for absolutely no error at all and the higher the values rise from zero, the more error the models have.

In order to determine the optimum number of nodes in the hidden layer of each of the four ANN models, a trial and error approach has been adopted. The statistical error in results has been observed for node numbers 1 to 20 in each model, increasing the number of nodes by 1 in every successive trial and keeping all the other model parameters constant. Finally, the optimum node number of hidden layer has been selected for which the model exhibited a minimum error. The various final criterias of the four ANN models developed are presented in Table 1.

Table 1 : Number of input, output & optimum hidden nodes of the developed ANN models

	Input nodes	Hidden nodes	Output nodes
Model-1	12	4	1 (Mirpur)
Model-2	12	11	1 (Mohammadpur)
Model-3	12	8	1 (Sutrapur)
Model-4	12	3	3 (Mirpur, Mohammadpur and Sutrapur)

Results & Discussion

After the completion of training, validation and testing of the ANN models for the whole dataset, input data has been used once again to bring out the outputs of the developed models. These outputs have been compared with their respective target data to calculate the values of R^2, MAE, MRE and RMSE.

Table 2 : Comparison of the efficiency of two types of modeling for Mirpur area

Statistical Indices	Individual Model	Combined Model
R^2	0.999898	0.999781
MAE (m)	0.141240	0.352780
MRE	0.005118	0.017058
RMSE (m)	0.204669	0.418202

Table 3 : Comparison of the efficiency of two types of modeling for Mohammadpur area

Statistical Indices	Individual Model	Combined Model
R^2	0.994183	0.989843
MAE (m)	0.280146	0.440368
MRE	0.020690	0.032428
RMSE (m)	0.475633	0.634284

Table 4 : Comparison of the efficiency of two types of modeling for Sutrapur area

Statistical Indices	Individual Model	Combined Model
R^2	0.889114	0.834943
MAE (m)	0.336271	0.816976
MRE	0.016731	0.065269
RMSE (m)	1.176936	1.473678

THE AUST
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Table 2 shows the performance of ANN models for Mirpur area, generated from the individual model (Model-1) and the combined model (Model-4). The R^2 value of the individual model (0.999898) appears to be higher than that of the combined model (0.999781), which indicates that the individual model yielded a better correlation between target/observed and output/anticipated groundwater level. From the comparison of values of MAE, MRE & RMSE of the individual and combined ANN models, it can be derived that the individual model performed better for all three study areas by causing lesser inaccuracy.

Similarly from Table 3 and Table 4, comparison of the data reveals that in both cases of Mohammadpur and Sutrapur area, the individual model shows a higher value of determination coefficient and lower values of different error criterion than that of the combined model. Thus it may be assumed that with the underlying conditions of ANN modeling observed in this study, a model consisting only one output for single area will yield a better result in forecasting groundwater level.

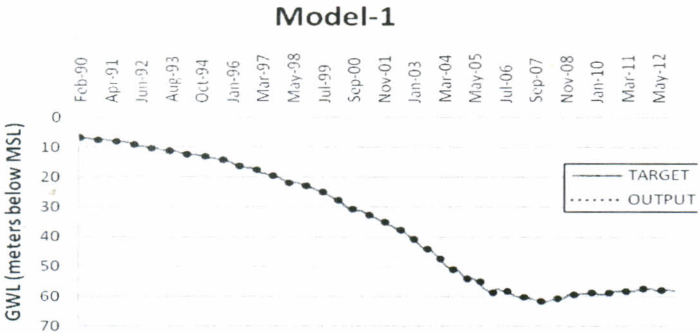

Figure 4: Plot of target and output values with time for Model-1(Mirpur)

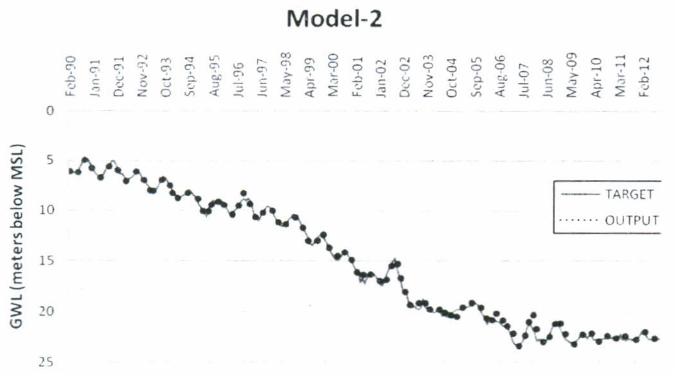

Figure 5: Plot of target and output values with time for Model-2 (Mohammodpur)

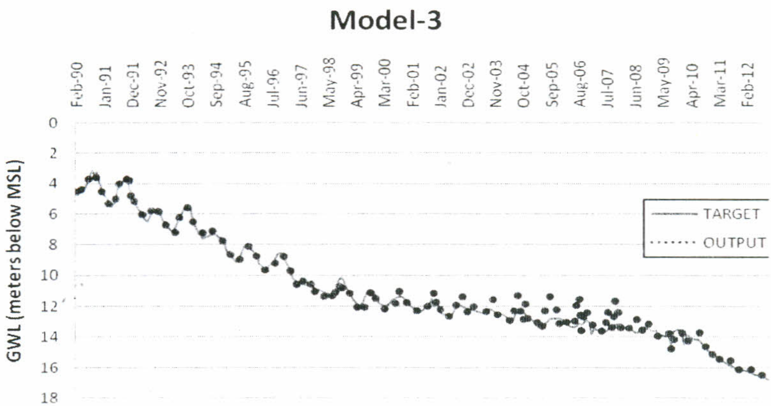

Figure 6: Plot of target and output values with time for Model-3 (Sutrapur)

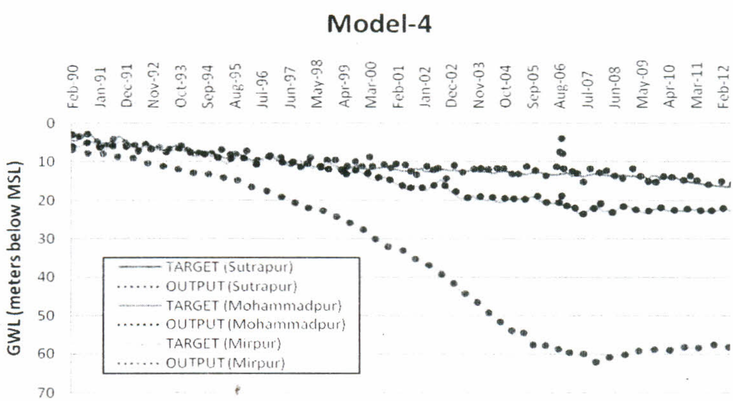

Figure 7: Plot of target and output values with time for Model-4 (combined)

In figures 4 to 7, plots are presented of target values of GW level and their corresponding output values of GW level of each of the models with time period. For Model-1, there seems to be an almost-perfect correlation between the target and output values. But for Model-2, there appears to be a decreased correlation between target and output values. For Model-3, the correlation is further degraded and it is the worst between the three models.

Though it has already been established from the statistical analysis tabulated in Table 2, Table 3 and Table 4 that the combined model fares worse results than the individual models, the trend of declining correlation from Model-1(for Mirpur) to Model-3(for Mirpur) is persistent in Model-4(whole Dhaka city), which can clearly be observed from Figure 7. In this final plot, the projected output and corresponding targets of Mirpur area have an almost perfect correlation, which decreases in the case of Mohammadpur, and decreases further in the case of Sutrapur, much like the scenario in the individual models.

The reasons behind this phenomenon could not be identified from this study as ANNs are data-driven mathematical models, and are unable to explain the underlying physical relationships between the inputs and outputs. This characteristic of ANNs may act as a blessing sometimes by allowing modeling to be done very easily, but it may also be seen as a limitation of such modeling, as in the case of this particular study. Though unexplained scientifically, it is assumed that the outputs of Mirpur area being better than the other two is because the input data provided has a better correlation with the drawdown characteristics and/or hydrogeological characteristics of that area.

Conclusion

Four artificial neural network models have been developed in this study to forecast the groundwater levels of three groundwater observation wells, representing three areas of Dhaka city of Bangladesh. The aim of the study was to compare the efficiency of artificial neural network models that forecast groundwater levels of single well with the models that predict groundwater levels of multiple wells at a time. By analyzing the results it has been observed that models with single output are more favorable than models with multiple output values. The authors suggest that future studies can be undertaken where instead of a feed-forward neural network or the Levenberg-Marquardt algorithm, other types of topologies and training algorithms are used in ANN modeling with a similar aim as this study to find out if the conclusion of those studies are similar to this study.

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