GROUNDWATER LEVELS ESTIMATION AT AREAS AFFECTED BY NEW NAGA HAMMADI BARRAGES USING ANN METHOD

Ahmed El-Tuhami* and Hassan I. Mohamed**

* Civil Eng. Department, EL-Azahar University, Kena Branch, Egypt
** Civil Eng. Department, Assiut University, Egypt
E-mail: hassanmohamed_2000@yahoo.com

ABSTRACT

During operation of New Naga Hammadi Barrages, the headpond will be maintained at a constant level of 65.9 m asl (above sea level). This is about 0.5 m higher than recent summer levels. This will cause a rise in groundwater levels, which are already high in some places. Also, this will be having indirect effects on plant growth (restricted rooting depth), soil quality (salinisation), public health (infectious diseases), and buildings (damp). Information on the groundwater levels is necessary in determining the agricultural lands needs of subsurface drainage network construction and soil properties. This paper presents an alternative to numerical groundwater models in the form of neural networks which is so useful tool because of the groundwater levels are affected by many unknown parameters which may vary in time and space due randomly variation of irrigation periods and existing of many canals and drains distributed in the area. A feed forward neural network model is developed to predict the groundwater levels at any place in the affected area by New Naga Hammadi Barrages from the specified values of water level in the Nile River upstream the barrage. Field measurements collected from observation wells network in the area extended from New Naga Hammadi Barrages to about 65 Kilometer upstream are used in training and testing the neural network. The validation of the developed network using observations data that were not involved in the training indicated the usefulness of the neural network approach for the prediction of the problem under consideration. Network-yielded values are found to be in well agreement with field measurements. Effect of the New Barrage on groundwater levels was predicted using the built-up neural network.

Keywords: Groundwater, New Naga Hammadi Barrages, ANN method.

1. INTRODUCTION

New Barrage is constructed at Naga Hammadi to replace the Old one. The maximum flood level upstream the New Barrage will be higher than the old one by 0.5. The direct impact of New Naga Hammadi Barrages will be on water levels in the river Nile upstream of the barrage. As the river is in hydraulic continuity with the underlying quaternary aquifer system, these changes in river level will impact directly on
groundwater levels. There is however also an indirect impact of river level changes on ground levels. Higher water levels in the River Nile will impede outflow from main drains that discharge to the Nile upstream of the barrage, Dawoud et al. (2006) and Farrag (2005). This impeded drainage will exacerbate backwater effects in the drains, thus increasing water levels in the drainage system. This increase in drain level will result in a rise in groundwater levels. Also, groundwater levels and depths are of interest because of their close association with soil quality, agricultural production, public health, and damp in buildings.

Many approaches in the past were used in simulating groundwater movements among of them Allam and Dawoud (2002), Moustafa (2000), Daliakopoulos et al. (2005); and Hamed and Hassan (2000). Parkin et al. (2007) presented an approach, which uses numerical modeling of generic river-aquifer systems to represent the interaction process, and neural networks to capture the impacts of the different controlling factors. Coppola et al. (2003) demonstrate the feasibility of training an ANN for accurately predicting transient water levels in a complex multilayered ground-water system under variable state, pumping and climate conditions. The ANN was trained to predict transient water levels in response to changing pumping and climate conditions. The trained ANN was validated with ten sequential seven-day periods and the results compared against both measured and numerically simulated ground-water levels. The results indicate that the ANN technology has the potential to serve as a powerful prediction and management tool for many types of groundwater problems.

The main scope of the present study is to develop quick and easy reliable method to predict the extent and magnitude of groundwater level changes as a consequence of river level changes after the operation of the new barrage. This will help in the planning of the future mitigation measures and the assessment of necessary compensation.

2. METHODOLOGY

Artificial Neural Networks (ANN) are nowadays one of the widely used modeling techniques which can approximate a non-linear relationship between input and output data sets without considering physical processes and the corresponding equations of the system. Since groundwater fluctuations are influenced by many interrelated hydrologic variables, which may vary in time and space, it is often necessary to use stochastic methods to describe the random nature of groundwater fluctuations. As a result, an ANN model is much faster than physically based model, which it approximates.
Feed-forward neural network (FNN)

Artificial neural networks are computing tools constructed of many simple interconnected elements called neurons with a unique capability of recognizing underlying relationship between input and output events. Figure (1) shows a typical neuron (Dayhoff, 1990). A neuron has two components (1) a weighted sum \( s = \sum w_i x_i + b \) that performs a weighted summation of the inputs \( x_1, x_2, x_3, \ldots, x_n \), where \( b \) is the bias of the network and (2) a linear, nonlinear or logic transfer function which gives an output corresponding to \( s \). Here, many kinds of functions, including threshold (logic) sigmoid, hyperbolic tangent, gaussian and linear could be used. In this paper, hyperbolic logarithmic (logsig) function \( f(x) = \frac{1}{1 + \exp(-x)} \) is applied for input and hidden layers. In addition, a linear transfer (purelin) applied for output layer. In a typical ANN, there are three types of neuron (Hsu et al. 1995): (a) input neurons that may receive external data, (b) output neurons that send data out of the ANN, and (c) hidden neurons whose signals remain within the ANN and connect the input layer neurons to output layer neurons (Fig. 2). Therefore, there are three types of layers corresponding to the types of neurons. The hidden neurons may form one or more hidden layers. The neurons in each layer are usually fully interconnected with neurons from neighboring layers. The importance of each inter-neuron connection is determined by its numerical value that is named weights. In feed-forward networks, model input data is processed forward through the network in sequential fashion independent of previous input data. The network prediction error information may, however, the propagated in a backward direction through the network. A three-layered back-propagation network structure is depicted in Fig. 2 (Dayhoff, 1990; Hsu et al., 1995).

![Figure (1): Basic components of a neuron.](image-url)
3. STUDY AREA AND DATA DESCRIPTION

The study area is located along the river reach between Naga Hammadi and Esna Barrages. The distance between the two barrages is 192.85 km. Upstream of the Naga Hammadi Barrages; a number of large cities are established. These include Naga Hammadi, Dishna, Qena and Luxor. The study area covers a distance of about 65 km upstream of the existing Naga Hammadi Barrages, as far as Dishna City as shown in Fig. (3). The area, which, is expected to be affected by the increasing water levels in the head pond of the new barrage, is located in the flood plain of the Nile River which has average level of approximate (67.00 m amsl) and 18 km wide. There are many canals and drains across this area with different degrees. A thirty observation wells are used in monitoring the ground water levels along the study area for the years 2005 and 2006 respectively. The data available are the co-ordinates of the observation well, the groundwater level in the wells and the monthly Nile water level upstream Naga Hammadi Barrages.
Figure (3): Study area, which extended from Naga Hammadi barrage to beyond Dishna City.

Old barrage

New barrage
4. RESULT AND DISCUSSIONS

The training and testing results obtained will now be used to form an ANN model that can be implemented to estimate groundwater levels for a variety of Nile water levels upstream New Naga Hammadi Barrages. The testing results are made known and to provide further validation of the ANN’s accuracy.

In this study, multiple hidden-layer ANN models consisting of two hidden layers were developed. The task of identifying the number of neurons in the input and output layers is normally simple, as it is dictated by the input and output variables considered to model the physical process. But as mentioned, the number of neurons in the hidden layers can be determined through the use of trial and error procedure (Mohamed and Hashem 2006). The optimal architecture was determined by varying the number of hidden neuron, and the best structure was selected. The training of the ANN models was stopped when either the acceptable level of error was achieved or when the number of iterations exceeded a prescribed maximum of 3000. The learning rate of 0.4 was also used. Three neurons were chosen in the input layer representing the well co-ordinates \((x, y)\) as a dimensionless variables and the water level in the Nile at the ordinate \(x\). One neuron in the output layer was selected to represent the water level at the observation well. The second layer (1st. hidden layer) consists of 20 neurons (chosen by trial) and the third layer consists of 35 neurons. The whole set of data is divided into two subsets, about 84% of the data for the training of the network (learning phase), and 16% to validate and test the network prediction. The logsig activation function is used as transfer function from the input layer to the hidden layer or from hidden layer to the next hidden layer and purlin activation function which a linear transfer function calculate the neuron’s output by simply returning the value passed to it, is used as transfer function from the last hidden layer to the output layer. All the computations are made with MATLAB® software (Release 7) and its neural modeling application. The training function used is (trainrp) that updates weight and bias values according to the resilient back propagation algorithm and it was found that it is faster than Levenberg-Marquardt optimization function.

The ANN results were plotted along with the known ground water levels. Referring to Fig. 4, the measured groundwater levels and that predicted by trained network, showed reasonably good agreement with measured data. The performance of ANN configurations was assessed based on calculating the mean absolute error (MAE), and the root mean square error (RMSE). The coefficient of determination, \(R^2\), of linear regression line between the predicted values from the neural network model and the desired output was also used as a measure of performance. The three statistical parameters used to compare the performance of the various ANN configurations are:

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - t_i|
\]
\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (o_i - t_i)^2} \]  
\[ R^2 = 1 - \frac{\sum_{i=1}^{N} (o_i - t_i)^2}{\sum (o_i - \overline{o_i})^2} \]

where \( o_i \) and \( t_i \) are target and network output for the \( i \)th output, and \( \overline{o_i} \) is the average of target outputs, and \( N \) is the total number of events considered.

The ANN configuration that minimized the two error measures described in the previous section (and optimum \( R^2 \)) was selected as the optimum. The whole analysis was repeated several times. Table (1) shows the error measures values for the built-up ANN model.

Table (1): Error values for the built-up ANN model.

<table>
<thead>
<tr>
<th></th>
<th>MAE</th>
<th>RMSE</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>0.1326</td>
<td>0.188</td>
<td>0.9891</td>
</tr>
<tr>
<td>Testing</td>
<td>0.2095</td>
<td>0.2607</td>
<td>0.9849</td>
</tr>
</tbody>
</table>

Figure (4): Estimated water levels using ANN model versus measured water levels for the trained data.
Test of ANN Model

With the training performed, it is necessary to test the networks. The testing phase examines the performance of model using the derived weights and measures the ability to classify the data correctly. Figure (5) shows a comparison between the estimated water level and the actual one. It is noticeable the well agreement between the measured water level and the computed one.

Figure (5): Estimated water levels using ANN model versus measured water levels for the tested data.

The application of the neural network model is illustrated by computing the ground water levels according to the new water levels in the Nile after the operation of the new barrage. Figure (6) shows values of groundwater levels after and before the operation of the new barrage through the year at well number PA03 (shown in Fig. 3). It is noticeable that the groundwater levels after the operation of the new barrage are higher than those before the operation of the new barrage. Also, Figure (7) shows a comparison between the groundwater level at the different observation wells before and after the operation of the new barrage at maximum pool level in Nile upstream the barrage.
5. CONCLUSION

Due to the direct hydraulic conductivity between the River Nile and the Quaternary system in the Nile Valley, increasing the headpond after the construction of the New Naga Hammadi Barrages will raise the groundwater levels upstream of the barrage.
The influence of the river level change upstream of Naga Hammadi Barrages extends as far as Dishna and extends over the full width of the Nile Valley. Currently groundwater is high in a large part of north Qena Governorate. This is mainly due to a combination of high volumes of irrigation and poorly functioning land drainage systems. The raised headpond will exacerbate this situation by further impeding land drainage and will affect the urban areas. Mitigation planning requires detailed knowledge of the size and location of changes in groundwater levels. Estimation of groundwater levels upstream of the barrage was carried out using an artificial neural network model. The model was built and tested using field observation well records for a period of year in the affected area. It was proved that ANN model superior in predicting ground water levels in areas characterizes by randomly distribution of sources of ground water recharge. The estimated model can be used in predicting groundwater level after the operation of New Naga Hammadi Barrages at any place and any time in the affected areas.

REFERENCES