Prediction of Groundwater Level in Safwan-Zubair Area Using Artificial Neural Networks

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***Abstract*-Safwan-Zubair area is regarded as one of the important agricultural areas in Basrah province, South of Iraq. The aim of this study is to predict groundwater level in this area using ANNs model. The data required for building the ANNs model are generated using MODFLOW model (V.5.3). MODFLOW model was calibrated based on field measurements of groundwater level in13 monitoring wells during a period of one year (Nov./2013 to Oct/2014). The neural network toolbox available in MATLAB version 7.1 (2010B) was used to develop the ANN models. Three layers feed-forward network with Log-sigmoid transfer function was used. The networks were trained using Levenberg-Marquradt back-propagation algorithm. The ANN modes are divided into two groups, each of four models. The input data of the first group include hydraulic heads, while, the input data of the second group include hydraulic heads and recharge rates. Based on results of this study it was found that; the best ANN model for predicting groundwater levels in the study area is obtained when the input data includes hydraulic heads and recharge rates of two successive months preceding the target month, the best structure of ANN model is of three layers feed-forward network type composes of two hidden layers, each of ten nodes, and the including of recharge rates as input data, beside the hydraulic heads has improved slightly the results.**

Keywords: Safwan-Zubair, Artificial Neural Network, MODFLOW.

I. Introduction

Safwan-Zubair area is regarded as one of the important agricultural areas in Basrah province because it is famous for producing the two crops of tomato and watermelon, in addition to the crops of onion, garlic eggplant, pepper, and cucumber. These crops cover the local consumption of Basrah as well as a part of the needs of the neighboring provinces. Agriculture in Safwan-Zubair area depends on irrigation using groundwater. As a result of the increasing demand for groundwater, particulary after the emergence of drought in Iraq accompained by scarcity of water, there is a great need for assessing groundwater availability in the study area.

Groundwater level is an indicator of groundwater availability. It can be monitored by direct observation of monitoring wells or by forecasting using simulation models. There are two kinds of groundwater simulation models; physical and mathematical models. Mathematical models can be subdivided into; numerical, analytical and statistical models. Artificial neural network (ANN) is one of statistical modeling techniques. It can be used to solve problems that are not amenable to conventional statistical and mathematical methods [1]. ANN is a relatively new approach for groundwater levels modeling and an attractive tool for traditional physical-based numerical models. A proper design of the ANN models architecture can provide a robust tool in water resources modeling and forecasting [2]. The advantages of adopting ANNs are [3]; (1) it is not necessary to characterize and quantify the physical properties in explicit way as in the numerical models and (2) the system can be modeled based on the simple quantifiable input variables.

The basic concept of ANNs was introduced by McCulloch and Pitts in 1943 [cited in 4]. An ANN is a computing model that tries to mimic the human brain and the nervous system in a very primitive way to emulate the capabilities of the human being in a very limited sense. It is a collection of simple, highly connected processing elements called neurons that respond (or "learn") according to sets of inputs. Each neuron receives input data, processes it, and delivers a single output. The ANN model is designed to identify the connection between input and output without going into analysis of the internal structure of the physical process. i.e., it is a black-box model. Selecting input variables is the most important step in ANN modeling [5]. The input data are usually obtained from historical field records. However, if field data is limited, the input data can be generated using a calibrated groundwater model, such as MODFLOW model [6]. The output can be the final product or it can be an input to another neuron.

MODFLOW is a modular three-dimensional finite-difference groundwater model developed by the U.S. Geological Survey, to describe and predict the behavior of groundwater systems. MODFLOW can simulate steady-state and transient flows in confined and unconfined aquifers with including the effects of wells, rivers, drains, head-dependent boundaries, recharge and evapotranspiration [7]. The solution consists of head (groundwater level) at every cell in the aquifer system at intervals called time steps.

Various models were developed before for groundwater level prediction using neural network methodology. Examples include those of; Nayak et al. [8], Affandi et al. [5], Feng et al. [9], Joorabch et al. [10], Sujatha and Kumar [11], Sirhan and Koch [3], Choobbasti et al. [12], Bisht et al. [13], Nyamathi [14], Kumar et al. [15], Chitsazan et al. [16] and Tapoglou et al. [17]. The most important output of these studies is that, the best ANNs structure for ground flow modeling needs to be examined for each study area.

The aim of this study includes developing a predictive model for groundwater flow in Safwan-Zubair area using artificial neural network. To achieve this aim, the objectives include; (1) application of MODFLOW model on the study area to collect the data necessary for ANN training, (2) collection of study area data based on field measurements and periodic meteorological records, (3) calibration of MODFLOW model and (4) development of ANN model for predicting the groundwater levels in the study area using Matlab 7.1.

II. LOCATION OF STUDY AREA

Safwan-Zubair area is located in south west of Basrah city, south of Iraq. It represents the southern sector of Western Desert bounded by latitudes (30º05'-30º25') and longitudes (47º30'-47º57'), Fig.(1). The study region covers about 1600km². There are two connected streams in this region, Shatt al-Basra canal and Khour Al Zubair estuary. These streams form the eastern boundary of the study area.

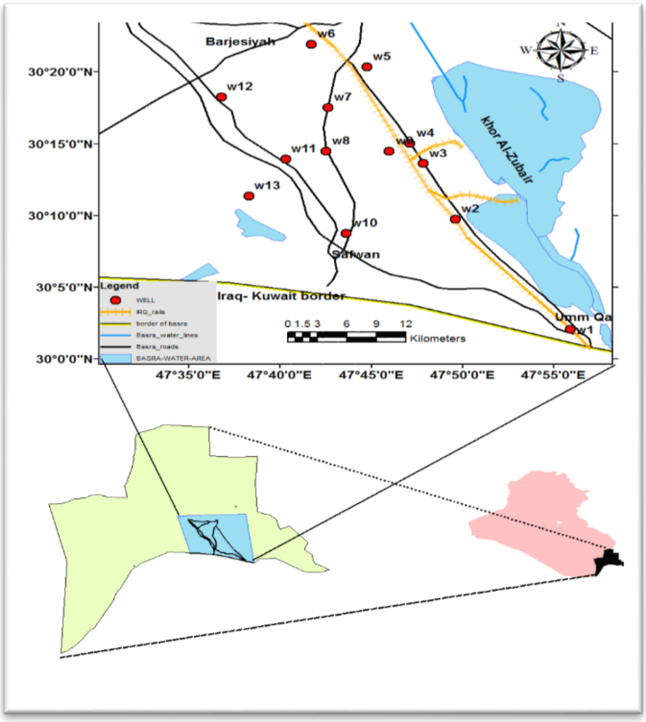

Fig. 1 Location of study area in reference to the map of Iraq.

III. APPLICATION OF MODFLOW ON STUDY AREA

MODFLOW uses finite difference method to solve the groundwater flow mathematical model. The spatial domain of the aquifer system in the study area was discretised using a square-centered grid. The grid consists of 80 columns and 80 rows. Where, the area of one cell is equal to (500 × 500m^2). Fig. (2) shows the model grid of the study area with the applied boundary conditions. From this figure it can be shown that; (1) the northern, southern west and southern boundaries of the study area were represented as no-flow boundaries, (2) to the east of the model area lies the canal of Shatt Al-Basra, therefore the eastern boundary was represented as constant head boundary, and (3) the western boundary was modeled as head-dependent boundary to allow inflow to the modeled region at a rate proportional to the head difference between the aquifer outside the simulated area and the model boundary.

In MODFLOW, the simulation time is divided into stress periods, which are, in turn, divided into time steps. In the present study, ten stresses periods are used, each of 30 days. During the first seven periods, there is direct recharge from rainfall, while, during the remaining five stress periods there is no recharge.

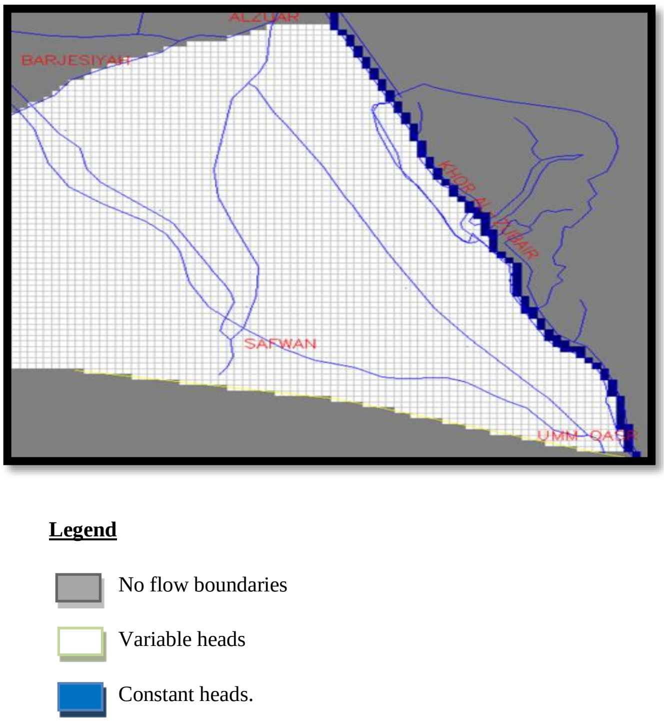

Fig. 2 Grid and boundary conditions of study area model.

IV. DETERMINATION OF DIRECT RECHARGE

Rainfall is source of groundwater recharge in the study area. It begins in October and continuous till April. The monthly average rainfall values in the study area during the period (Nov./2013- Oct./2014) are shown in Fig.(3). The direct recharge to groundwater as a percentage of rainfall was estimated using Cumulative Rainfall Departure (CRD) method. The CRD formula is defined as [18]:

$$CRD(i) = \{\sum_{i=m}^{n} Pi - \left(2 - \frac{1}{Pav}\sum_{i=m}^{n} Pi\right)\sum_{i=m}^{n} Pt\} \quad \ldots(1)$$

(i=1, 2, 3,..I) (n=i, i−1, i−2, ..N) (m=i, i−1, i−2, ..M)m<n<I

where:

CRD (i): is the cumulative recharge from rainfall event of m to n,

I: is the total length of rainfall series,

Pi: is the rainfall amount at ith time scale (daily, monthly or annually),

Pav: is the mean precipitation of the whole time series,

Pt: is a threshold value representing the boundary conditions (Pt ranges from 0 to Pav).

The application of CRD formula on the study area, with using the rainfall data shown in Fig. (3), gives a recharge percentage of 20%.

V. FIELD DATA COLLECTION

The levels of groundwater in the study are necessary for calibrating the MODFLOW model. Thus, field work has been conducted to measure the levels of groundwater. The field work was started on November/2013 and finished on

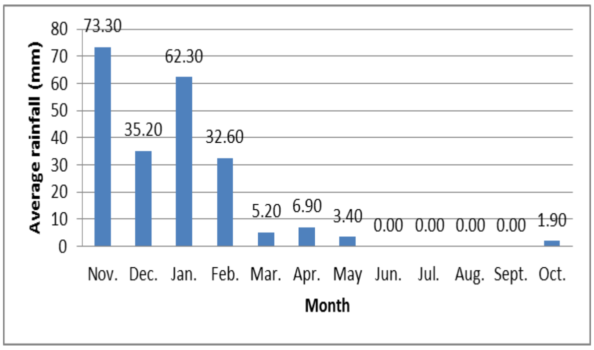

Fig. 3 Distribution of monthly average rainfall during the period (Nov./2013-Oct./2014).

October/2014. Thirteen monitoring wells were selected for measuring the groundwater levels on monthly basis. The layout of these wells in model grid is shown in Fig. (4).

The instruments used to conduct the field work, include; Differential Global Position System (DGPS) type TRIMBLE and GPS by hand for specifying the coordinates and ground level of wells location, and laser measurement tape and Eco sounder for measuring the water depth in each well. The Field work has been performed in accordance to the following procedure:

1. Measurement of water depth in one of the thirteen wells using Eco sounder.
2. Setup of DGPS near one of the thirteen wells, which includes;.
   i. Setup of DGPS receiver. The receiver was set in accordance with manufacturer's specifications prior to beginning of any observations. To eliminate any possibility of missing the beginning of the observation session, all equipment was setting up with power supplied to the receiver at least five minutes prior to the beginning of the observation session.
   ii. Setup of Antenna. All the used tri-braches were calibrated and adjusted periodically to insure accuracy.
3. Measurement of instrument height (HI). Height of instrument HI refers to the correct measurement of the distance of the GPS antenna above the reference (any monitoring well position). HI is measured before and after each observation session.
4. Storing of obtained data in DGPS memory which includes HI, start time of observation, end time of observation, etc.
5. Repeat steps (1-4) to the other twelve wells. Where the work duration of one well location is about 3 hours. That time is required to grantee the passing of satellite over the area.
6. Send the obtained data of each well to Online Positioning User Service (OPUS). OPUS provides simple access to high-accuracy National Spatial Reference System (NSRS) coordinates. After uploading the data file collected with a DGPS receiver, the NSRS position is obtained via email. The email includes corrected coordinates of well location, ellipsoid and geoid heights, and corrected ground level.
7.

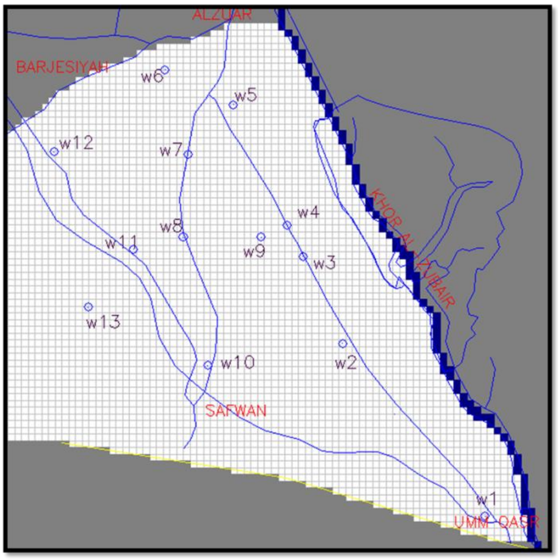

Fig. 4 Layout of monitoring wells on MODFLOW model grid.

VI. CALIBRATION OF MODFLOW MODEL

Calibration of MODFLOW Model

MODFLOW model has been applied to simulate the unsteady groundwater flow in the study area. The model was calibrated by changing the values of hydraulic conductivity and specific yield. The unsteady state calibration results were evaluated by comparing the temporal variation of simulated heads with those of observed ones at the thirteen observation wells. The best results of hydraulic heads distribution in the study area were obtained by adopting the calibrated values of hydraulic conductivity values vary over the range (55-190) m/day and specific yield values vary over the range (0.12-0.49).

VII. BUILDING OF ANN MODEL

The neural network toolbox available in MATLAB version 7.1 (2010B) was used to develop ANN model for predicting the groundwater level (or hydraulic head) in Safwan- Zubair area. Three layers feed- forward network with Logistic sigmoid transfer function was used. The network was trained using Levenberg-Marquradt (LM) back-propagation algorithm. This algorithm is efficient in predicting ground- water level as indicated by many researchers like Affandi et al. [5], Joorabchet al. [10], Sujatha and Kumar [11], Choobbasti et al. [12], Kumar et al. [15], Chitsazanet al. [16], and Tapoglou et al. [17].

The input data for ANN development was generated using the calibrated MODFLOW model (V5.33). Excluding the boundary values, MODFLOW model generates 3797 hydraulic head values for the study area during each month. 70% of these values (2657 samples) was used for ANN model training, 15% of these values (570 samples) was used to measure network generalization and to halt training when generalization stops improving, and the remaining percent of values (570samples) was used to measure the network performance after training. The best network architecture was selected by trial and error procedure based on Mean Square Error (MSE) and coefficient of correlation (R).MSE and R are calculated as [19];

$$MSE = \frac{\sum_{i=1}^{n}(x_i - yi)^2}{n} \tag{2}$$

$$R = \sqrt{1 - \frac{\sum(x_i - yi)^2}{\sum x_i{}^2 - \frac{\sum yi^2}{n}}} \tag{3}$$

where x_i is actual data and y_i is calculated data by network and n is the number of data. Zero is the best condition for MSE and one is the most desirable condition for R.

Two groups of ANN models were built to predict the groundwater levels in the study area. The first group includes four models (No.1 to No.4). These models were trained using one and two hidden layers with the hydraulic head is the input. The second group includes, also, four models (No.5 to No.8) which were trained using two hidden layers with hydraulic head and recharge as inputs. The output (target) of the two model groups is the hydraulic head.

VIII. Results and Discussion

As indicated in the previous section two groups of ANN models were examined for predicting groundwater level in Safwan-Zubair area. The first group includes models No.1, 2, 3, and 4. For each of these models, six structures were examined; one hidden layer with two nodes, one hidden layer with five nodes, one hidden layer of ten node, two hidden layers each of two nodes, two hidden layers each of five nodes, and two hidden layers each of ten nodes. In model No.1, the hydraulic heads of November are used as input variables, while, the hydraulic heads of December are used as target values. Fig. (5) shows the structure of this model when ANN of two hidden layers each of ten nodes is adopted.

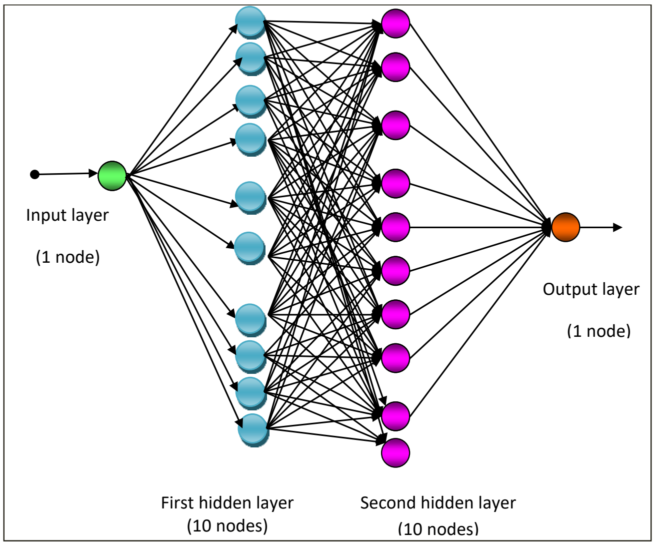

Fig. 5 Configuration of ANN with input layer of one node and two Hidden layers, each of ten nodes

Table I presents training results, in terms of R and MSE values, of all structures of ANN model No.1. This table shows that R values for all structures are greater than 0.9. Also, it indicates that the best values of statistical parameters are obtained for ANN model No.1 with two hidden layers, each of ten nodes. The best R value for the regression line that represents the relation between the targets and the outputs is 0.9145. The corresponding R-values for the training, validation and test are 0.9133, 0.9189 and 0.9164, respectively, with MSE of 0.026. Figs. (6) and (7) present the regression plots for the relations between targets and outputs (predicted groundwater levels in the study area) using the best structure (two hidden layers, each of 10 nodes) of ANN model No.1.

In model No.2, the hydraulic heads of two successive months (December and January) are used as input variables, while, the hydraulic heads of February are used as target values. Table II presents training results, in terms of R and MSE values, of all structures of ANN model No.2. This table shows that R values for all structures are approximately equal to 1 (perfect fit). Also, it indicates that the best values of statistical parameters are obtained for ANN model No.2 with two hidden layers, each of ten nodes. The best R value for the regression line that represents the relation between the targets and the outputs is 0.9999. The corresponding R-values for the training, validation and test set are 0.9999, 0.9999 and 0.9999, respectively, with MSE of 1.25×10^{-6}.

In model No.3, the hydraulic heads of three successive months (April, May and June) are used as input variables, while, the hydraulic heads of July are used as target values. Table III presents training results of model No.3. This table shows that R values for all ANN structures are low as compared with those of model Nos. 1 and 2. Also, it indicates that the performance of ANN with one hidden layer of ten nodes is nearly similar to the performance of two hidden layers, each of ten nodes, but the last has lower MSE value. The low R values can be attributed to the nature of input and target data. The input data includes the hydraulic heads of April, May, and June. During this period, the study area is under the influence of recharge and discharge. But, the target data includes the hydraulic heads of July which is a month of relaxation period (period of no recharge and discharge).

In model No.4, the hydraulic heads of four successive months (April, May, June, and July) are used as input variables, while, the hydraulic heads of August are used as target values. Table IV presents training results, in terms of R and MSE values, of all structures of ANN model No.4. This table shows that R values for all structures are greater than 0.9. Also, it indicates that the best values of statistical parameters are obtained for ANN model No.4 with two hidden layers, each of ten nodes. The best R value for the regression line that represents the relation between the targets and the outputs is 0.955. The corresponding R-values for the training, validation and test set are 0.956, 0.959 and 0.948, respectively, with MSE of 0.007.

The second ANN models group includes models No.5, 6, 7, and 8. All of these models were built using the best structure obtained from the first models group which is of two hidden layers each of ten nodes. The input data of these models includes hydraulic heads and recharge rates and the output data include hydraulic heads as shown in Table V. The training results of second group of ANN models are shown in Table VI. From this table it can be shown that model No.6 have the maximum R value (equals 1), which represents the best fit between the outputs and targets, and the minimum MSE value (equals 1.75×10^{-8}). While, model No.7 has the minimum R (equals 0.63) value and the maximum MSE value (equals 0.06). The bad performance of model No.7 is attributed to the variation of hydraulic conditions during the months of input data and the month of target data. The regression plots of models No.6 are shown in Figs (8) and (9).

TABLE I
TRAINING RESULTS OF ANN MODEL NO.1

Number of hidden layer	Number of nodes in hidden layer	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE
One	Two	0.9099	0.9077	0.9095	0.909	0.027	136
	Five	0.9087	0.9256	0.9023	0.910	0.029	6
	Ten	0.9158	0.9069	0.8985	0.912	0.033	68
Two	Two	0.913	0.9059	0.905	0.911	0.030	297
	Five	0.9128	0.9089	0.9202	0.9135	0.029	14
	Ten	0.9133	0.9189	0.9164	0.9145	0.026	10

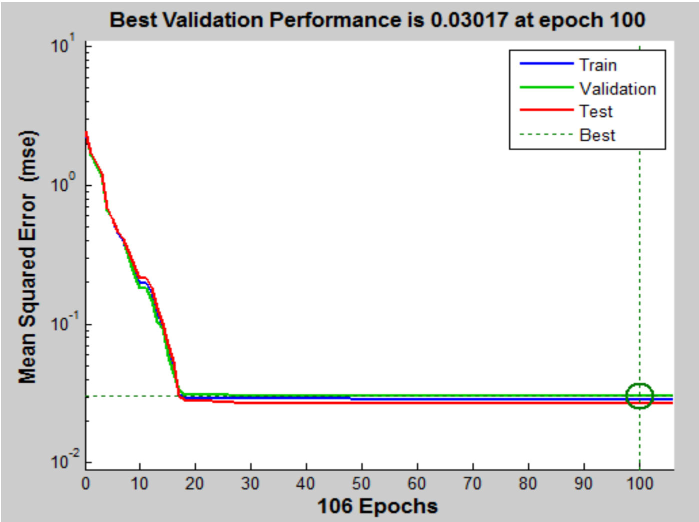

Fig. 6 R values for ANN model No.1 with two hidden layers, each of ten nodes

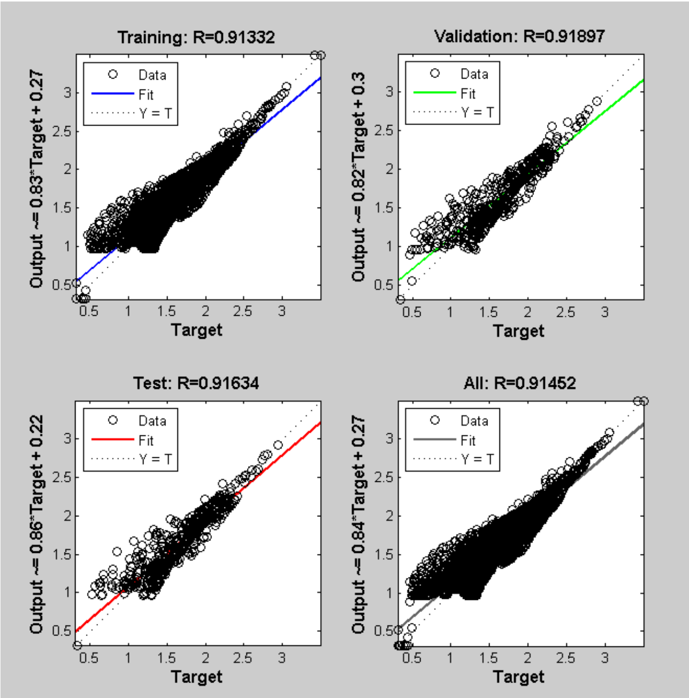

Fig. 7 MSE versus epochs for ANN model No.1 with two hidden layers, each of ten nodes

TABLE II

TRAINING RESULTS OF ANN MODEL NO.2

Number of hidden layer	Number of nodes in hidden layer	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE
One	Two	0.9998	0.9999	0.9997	0.9998	2.9×10^{-5}	304
	Five	1	0.9999	1	1	3.1×10^{-5}	726
	Ten	0.9999	0.9998	0.9999	0.9999	4.32×10^{-5}	11
Two	Two	0.9998	0.9999	0.9998	0.9998	3.4×10^{-5}	483
	Five	0.9999	0.9999	0.9999	0.9999	8.12×10^{-6}	226
	Ten	0.9999	0.9999	0.9999	0.9999	1.25×10^{-6}	26

TABLE III
TRAINING RESULTS OF ANN MODEL NO.3

Number of hidden layer	Number of nodes in hidden layer	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE
One	Two	0.5989	0.6324	0.6752	0.6164	0.0653	58
	Five	0.6480	0.5827	0.5625	0.626	0.071	144
	Ten	0.6376	0.5978	0.6122	0.6278	0.064	9
Two	Two	0.6131	0.6004	0.6428	0.6162	0.071	23
	Five	0.6367	0.5970	0.6059	0.6263	0.064	21
	Ten	0.6367	0.5599	0.632	0.6264	0.063	13

TABLE IV
TRAINING RESULTS OF ANN MODEL NO.4

Number of hidden layer	Number of nodes in hidden layer	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE
One	Two	0.947	0.937	0.939	0.945	0.013	43
	Five	0.951	0.952	0.950	0.951	0.0099	44
	Ten	0.954	0.951	0.953	0.952	0.0088	41
Two	Two	0.946	0.945	0.950	0.946	0.0084	56
	Five	0.955	0.943	0.961	0.954	0.0083	48
	Ten	0.956	0.959	0.948	0.955	0.007	41

TABLE V
INPUT AND TARGET DATA OF MODELS NOS.5 THROUGH 8

Model No.	Input data	Target data
5	Hydraulic heads and recharge rate of Nov.	Hydraulic heads of Dec.
6	Hydraulic heads and recharge rates of Dec. and Jan.	Hydraulic heads of Feb.
7	Hydraulic heads and recharge rates of Apr., May and Jun.	Hydraulic heads of Jul.
8	Hydraulic heads and recharge rates of Apr., May, Jun., and Jul.	Hydraulic heads of Aug.

TABLE VI
TRAINING RESULTS OF ANN MODELS NOS.5 THROUGH 8

Model No.	R-Train	R-Validation	R-Test	R-All	MSE	Epoch-MSE
5	0.946	0.945	0.95	0.94	0.019	10
6	1	1	1	1	1.75×10^{-8}.	73
7	0.622	0.637	0.653	0.63	0.06	17
8	0.960	0.958	0.97	0.962	0.008	48

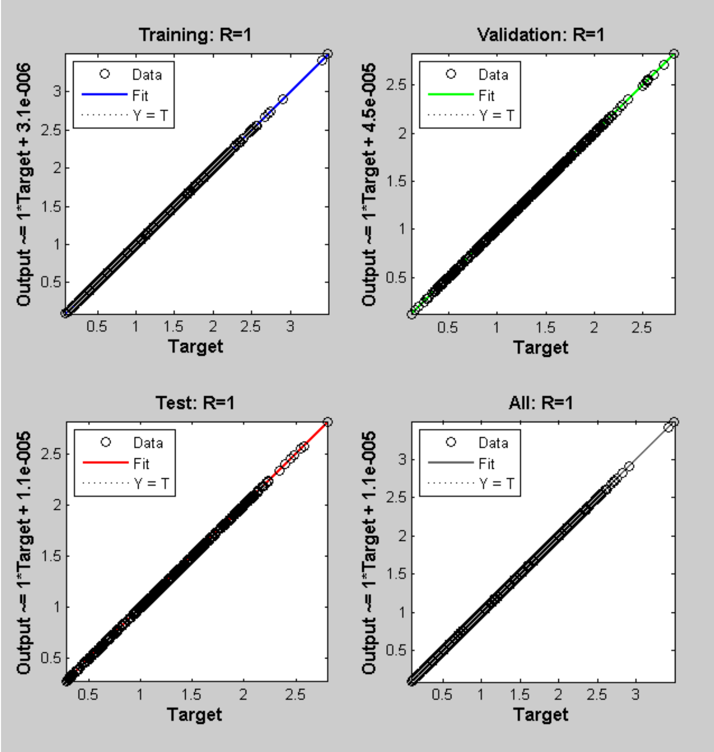

Fig. 8 R values for ANN model No.6

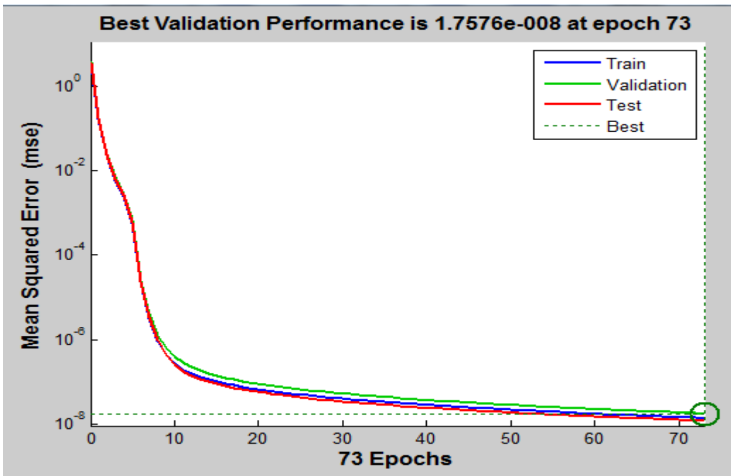

Fig. 9 MSE versus epochs for ANN model No.6

The performance of the eight ANN models has been compared in terms of correlation coefficient (R) and mean square error (MSE) values as shown in Figs. (10) and (11). These comparisons are for the best ANN structure which is composed of two hidden layers, each of ten nodes. Fig. (10) shows that model No. 6 has the highest R value which is equal to1 (best fit of ANN outputs and the target values). Fig.(11) shows that model No.6 has the lowest MSE value which is 1.75×10^{-8}. Thus the best ANN model for predicting ground water levels in Safwan-Zubair area is when the input data includes hydraulic heads and recharge rates of two successive months preceding the target month.

In general, by comparing the results of the first models group (model Nos.1, 2, 3, and 4) with those of the second group (model Nos.5, 6, 7, and 8), it can be noted that the including of recharge rates as input data to the ANN models has improved slightly the results.

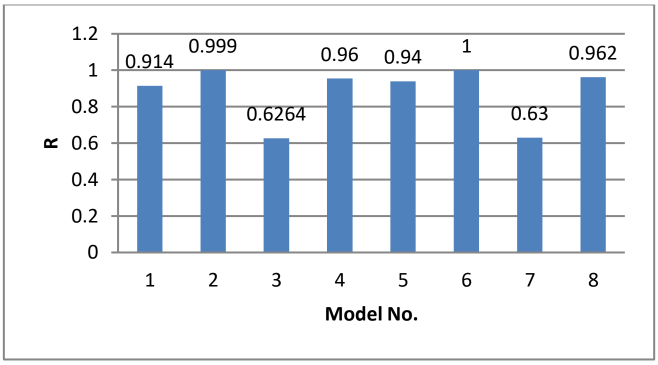

Fig. 10 Comparison of R values of the different ANN models

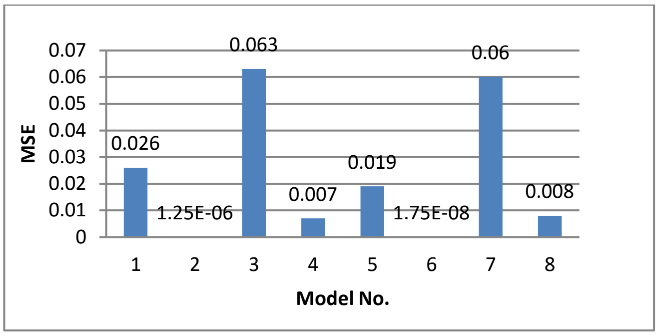

Fig. 11 Comparison of MSE values of the different ANN models

IX. Conclusions

Based on building of eight ANN models for predicting groundwater levels in the Safwan-Zubair, it was found that;

1. The best ANN model for predicting groundwater levels in the study area is obtained when the input data includes hydraulic heads and recharge rates of two successive months those preceding the target month. The correlation coefficient and mean square error of this model is 1 and 1.75×10^{-8}, respectively.
2. The best structure of ANN model for predicting groundwater flow in the study area is of three layers feed- forward network type composes of two hidden layers, each of ten nodes. This ANN model is developed with Logistic sigmoid transfer function and trained using Levenberg-Marquradt (LM) back-propagation algorithm.
3. The including of recharge rates as input data, beside the hydraulic heads, to the ANN models has improved slightly the results.

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