A Comparative Study of Adaptive Neuro Fuzzy Inference System and Artificial Neural Networks for Predicting Groundwater Hydraulic Head in an Arid Region

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Abstract

The aim of this research is to develop a predictive model to estimate the groundwater head in Safwan-Zubair area by using an adaptive neural fuzzy inference system (ANFIS). This area represents the southern sector of the Iraqi Desert, an arid region with scarce and limited resources. The data required for building the ANFIS model are generated using MODFLOW model (V.5.3). MODFLOW model was calibrated based on field measurements during one year. MODFLOW model generated (3797) hydraulic head values during each month. 70% of these values (2658 samples) was used for training, 30% of these values (1139 samples) was used for checking. The accuracy of the ANFIS models are compared with previous work based on artificial neural network (ANN) technique. Different combination of successive hydraulic heads and recharge rates of groundwater is used as input variables. There is no significant increase in the estimation accuracy when adding another input variable (recharge rate). Because the amount of this variable is very little, so its influence on the results was imperceptible. A comparison of ANFIS and ANN shows that the ANFIS model performs preferable than the ANN model on the checking phase. ANFIS model combines both fuzzy logic basics and neural networks; thus their properties can be utilized in one frame. It can be concluded, the ANFIS model appears to be more convenient than the ANN model for predicting groundwater hydraulic head from related input data.

Key words: ANFIS; ANN; Numerical modeling; Groundwater hydraulics; Iraq.

1. Introduction

Groundwater plays a key role in water sources around the world and it is important for a number of many purposes, such as for domestic, agriculture, and industrial uses. Management and predicting the quantity amount of groundwater is an important process to meet the future demand. With the development of lifestyle, there is a growing demand for water resources. Prediction and optimal management of groundwater must be developed by decision makers to optimally utilize these resources because of some anthropogenic causes such as industrialization and unplanned domestication, it was found that there is continued to dispel the amount of groundwater [1].

In arid and semiarid climates, where aquifers don't have any interaction between surface water and groundwater in addition to a tiny amount of annual rainfall ; these aquifers receive little recharge, where it has more complicated of properties than in classical sedimentary media. Suitable management and modern techniques are thus required to manage them. Groundwater modeling was used over the past two decades, especially after the rapid development of computer technology, many difficult questions in the hydrogeological investigation has answered by modeling of groundwater. Groundwater modeling is a process to represent an areal system in another form such as mathematical form or physical form to investigate the system's response under certain conditions, or to predict the behavior of the system in the future [2]. Groundwater models are used to estimate the rate and direction of groundwater movement through aquifers and confining units under the ground surface, it is an active tool for water resources management, groundwater simulation and remediation. In last three decades, MODFLOW and other models have been used in groundwater modeling as an effective tool for prediction and simulation of groundwater flow [3 through 9].

For developing a traditional numerical model, more investigation site and comprehensive study for detailed and reliable input parameters are required. Multi layers with complex structures of the aquifers, including the complex estimation of groundwater heads can be depicted by conventional numerical methods [10]. For developing numerical model that needs an accurate and extensive information requiring great effort because of the spatial variability, characteristics of hydrogeology and their availability. Empirical models and black box models usually require less effort and less data compared with physically based models. Unlike conceptual modeling, no hydrological parameters are need to drive functional relationships between the independent and the dependent variables; these are determined automatically in the calibration process. Artificial neural network (ANN) models and fuzzy inference system (FIS) models are one of these models, which are treated as universal approximates and is very suitable for dynamic nonlinear system modeling. In last decades, many engineers and hydrologists have tried to use modern data driven techniques to predict water resources behavior, including ANN and FIS. Many models have been developed to simulate groundwater flow using ANN [11 through 24].

Artificial intelligence techniques, such as the fuzzy inference system (FIS), it is an effective and efficient technique for forecasting groundwater levels. The adaptive neuro fuzzy inference system (ANFIS) is a multi-layer feed forward network that uses algorithms of neural network and fuzzy logic to set the input space to the output space. With the ability and possibility for combining the numeric power of a neural network and verbal power of a fuzzy system, ANFIS has been shown to be effective in modeling numerous processes in hydrology and water resources engineering. ANFIS possesses good ability of learning, constructing, expensing, and classifying. It has the ability for extracting of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base [25]. In the last decade, some researches dealt with predications of groundwater by using ANFIS [26 through 33].

The first phase of this study is to develop a predictive model to predict the groundwater head in Safwan-Zubair area, Basrah province, south of Iraq, by using an adaptive neural fuzzy inference system (ANFIS). The data required for building the ANFIS models are generated using MODFLOW model (V.5.3). MODFLOW model was calibrated based on field measurements during one year. While, the second phase in this study, the results of the ANFIS models are compared with previous work based on artificial neural network (ANN) technique.

2. The Study Area

The study area is located in southern Iraq. It lies between longitude line [47o30'– 47o55'] and latitude line [30o03'– 30o25'] and considered area is about 1400 km2 as shown in Figure 1. This area occupies the southern part of the Iraqi desert, an arid region with scarce and limited resources. In the absence of a permanent river, groundwater is an essential natural water resource in this area. It is an important agricultural and industrial area in which the groundwater is the prime source for domestic and irrigation. The upper part of Dibdibba Formation represents the most important aquifer in the study area. Dibdibba formation consists of sand – gravel soil with raising the level of ground surface toward the west and southwestern. It is unconfined with average thickness of 14m. Because of the emergence of drought in Iraq that is accompanied with scarcity of water, there is an insistence requirement for evaluation of groundwater availability in Safwan Al-Zubair area.

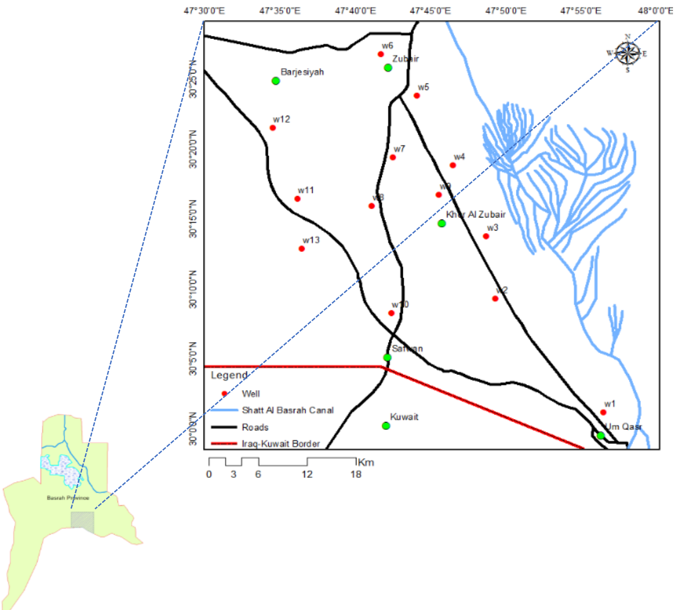

Figure 1. Location of study area and monitoring wells in Reference to the map of Basrah Province.

3. Application of Modflow

A finite difference two-dimensional model is used for modeling the groundwater flow for the upper aquifer in the study area. In other word, this simulation is fixed for upper layer only. The base of the upper aquifer is assumed as an impermeable boundary and there is no moving of groundwater in vertical direction ($\partial h/\partial z = 0$) i.e. The activity of the deep aquifer is negligible. Figure 2 shows the spatial distribution of the existing wells in the study area. The locations of these wells were obtained from Wateriness Resources Directorate/ Groundwater Branch in Zubair City for the year 2014. The groundwater is abstracted by the hand-dug and tube wells, this water are used for domestic and agricultural purpose. Generally, the large diameter hand dug wells that are conducted randomly with non-uniform shapes, are mostly used for abstract groundwater as a comparison with tube wells. There are five hundred penetrate wells. The maximum and minimum values of the pumping rate are (1209.6m3/day) and (43.2m3/day), respectively. An 84% is the percentage of irrigated water that returns back to the groundwater system, because the soil retains water only for a very short period of time [34]. Propagation of the trickle irrigation system led to decreasing in this percentage that is contributed to evapotranspired instead of infiltrated into the groundwater system [35]. 70% is used to represent the quantities of water that percolated to the groundwater from irrigation water and only 30% of water is consumed.

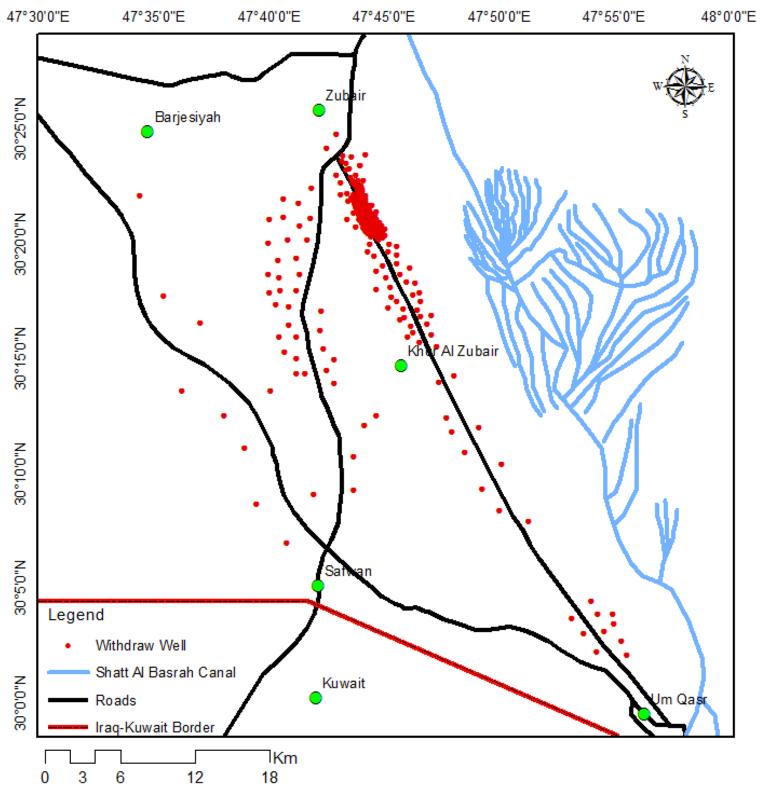

Figure 2.Spatial distribution of existing wells in the study area

The grid in present model consists of 80 columns and 80 rows. In which, the area of each cell is about (2500m2). The east portion of the model area locates the canal of Shatt Al-Basrah, for this reason, the eastern boundary was assumed to be a constant head boundary, while the western boundary was represented as head dependent boundary to allow inflow to the study area at a rate proportional to the difference in head between the model boundary and the aquifer outside. Based on groundwater flow contour map, southern west and southern boundaries of the study area were represented as non-flow boundaries.

Thirteen monitoring wells were selected for measuring the groundwater levels on monthly basis for one year (see Figure 1). Field work has been conducted to measure the head of groundwater for the period from November/2013 to October/2014. The instruments used to conduct the field work, include; Differential Global Position System (DGPS) type TRIMBLE, GPS by hand for specifying the coordinates and ground level of wells location, laser measurement tape and Eco sounder for measuring the water depth in each well [24].

In the present study, the unit time of simulation is days, nine stresses periods are used based on direct rate recharge and pumping period. The seven stress periods are represents the winter season (November up to May), this mean that each period has duration of 30 days with specific value of direct recharge rate. The amount of direct recharge changes with time during the seven stress periods. Normal pumping periods have been almost in November up to May, they attain about twelve hours per day. The eighth stress period represents extensive pumping periods are during the months of August, September and October, they attain about twenty hours per day. The ninth stress period represents relaxation periods are an approximately the two months June and July, where irrigation activities are stopped. The calibrated values of hydraulic conductivity vary over the range (15-150) m/day. While, the calibrated values of specific yield vary over the range (0.125-0.45).

4. Results And Discussion

Adaptive neural fuzzy inference system approach available in MATLAB version 7.1 (2010B) is employed in this present study to observe its applicability on prediction of monthly groundwater hydraulic head. In the ANFIS model, one of the most significant step in the development of the pathological prediction model is the selection of input variables. These variables define the model structures and the results of the modeling process. The input data for ANFIS development was generated using the calibrated MODFLOW model (V5.33). MODFLOW model generates (3797) hydraulic head values for the study area during each month. 70% of these values (2658 samples) was used in training phase, 30% of these values (1139 samples) was used in checking phase. Root mean squared error (RMSE), mean obsolete error (MAE), determination coefficient (R2), correlation coefficient (R) are used as evaluation criteria. The RMSE shows a good fit related to high values whereas the MAE measures a more balanced perspective of good fit with moderate value. The R2 indicates the degree of correlation of two variables linearly. R is a measure of the extent to which trends are tracked in the expected value of trends in the previous actual value.

The clustering algorithm is used in this research, it is a method which is usually employed to discover a cluster center and define the position the center of each cluster [36], by this method, the data points of the populate some multidimensional space can be grouped into a specific number of different clusters [37]. Subtractive clustering algorithm is used for determining the cluster number and cluster center location, which is an attractive approach to the synthesis of ANFIS. Each sample points meet in the form of cluster groups. Clustering radius parameter (r) determines the number of clusters and rules of fuzzy if-then in subtractive clustering method. This parameter is change from (0) to (1). Based on adjusting clustering radius, the training error can be controlled. Smaller clusters and more rules are created from smaller cluster radius, where large cluster and few rules are generated from large cluster radius. According to the evaluation criteria (RMSE), the best ANFIS model is selected. By trial and error, optimal cluster radius is calculated by implementing a network of subtractive cluster for several times, the number of if-then rules is changed with range of clustering radius value (0, 1).

The input data was normally distributed by using the Gaussian function f(x) as in the following formula:

$$f(x) = \frac{e^{-(x-\mu)^2/\sigma^2}}{\sigma\sqrt{2\pi}} \qquad (1)$$

Where, μ and σ : mean and standard deviation of data, respectively of normal distribution. The cluster center is represented by the mean, while; the standard deviation is determined by the following function.

$$\sigma = (\mathrm{radii} \times (\max(\mathrm{data}) - \min(\mathrm{data})))/\mathrm{sqrt}(8.0) \qquad (2)$$

The present study is compared with previous study that done by Al-Aboodi et al. 2016. Two groups of ANN models were built to predict the groundwater heads. The first group includes three models (from No.1 to No.3) with only one input value (hydraulic head). While, the second group includes, also, three models (from No.4 to No.6) with two input values (hydraulic head and recharge). In the model No. (1), the hydraulic heads of November are used as input variables, while, the hydraulic heads of December are used as target variables. Table 1 shows the best value of clustering radius (0.1) is associated with lowest value of checking root mean squared error (chRMSE, 0.021) for model no.1.

Table 1. r, RMSE and no. of rules of model no.1

r	chRMSE	No. of rules
0.1	0.021	11
0.2	0.0324	6
0.3	0.0399	4
0.4	0.0387	4
0.5	0.0216	2
0.6	0.0227	2
0.7	0.0242	2
0.8	0.0262	2
0.9	0.0280	2

Membership function (mf) is a linear equation; this equation is consisted from equation parameters multiply by input variable for example, output mf1 in model No.1

$$\text{Output } mf_1 = C_1 * H_{Nov} + C_2 \quad (3)$$

In this equation, parameter C1 is coefficient corresponding to the groundwater hydraulic head at November (HNov), while C2 is constant in each equation. Table 2 is illustrated the Gaussian membership function parameters for the ANFIS model no.1.

Table 2. Input (a) and output (b) membership functions parameters of model no.1

a			a		
input	H_{Nov}		input	H_{Nov}	
Parameter	σ	μ	Parameter	σ	μ
mf1	0.08326	1.845	mf7	0.08326	1.55
mf2	0.08326	1.391	mf8	0.08326	3.178
mf3	0.08326	2.035	mf9	0.08326	2.979
mf4	0.08326	2.514	mf10	0.08326	2.376
mf5	0.08326	1.698	mf11	0.08326	2.718
mf6	0.08326	2.246			
b			b		
output	HDec			HDec	
Parameter	C1	C2	Parameter	C1	C2
mf1	1.125	-0.235	mf7	1.281	-0.4315
mf2	1.058	-0.0528	mf8	0.9392	0.2391
mf3	1.018	-0.0276	mf9	0.974	0.1218
mf4	1.065	-0.1473	mf10	1.129	-0.2941
mf5	1.345	-0.5932	mf11	1.067	-0.1494
mf6	1.113	-0.2409			

The details of other models for the first group that include the input, target, and the best value of clustering radius that associated with lowest value of checking root mean squared error are shown in Table 3.

Table 3. Input, target, r, chRMSE, and number of rules of other models in the first group.

Model No.	Input (hydraulic head)	Target (hydraulic head)	r	chRMSE	No. of rules
Model No. 2	Apr, May, Jun	Jul	0.7	0.0021	3
Model No. 3	Apr, May, Jun, Jul	Aug	0.2	0.0422	8

Table 4 shows the comparison between the current study that conducted by using ANFIS and pervious study were presented by Al Aboodi et al 2016 which it's conducted by using ANN. Two statistical parameters are used as comparison criteria. These statistical parameters are mean squared error (MSE) and coefficient of correlation (R). There is a important improvement in the models performance when comparison with ANN models, by reducing MSE by (83.04%) and increasing R by (9.02%) for model no.1. There is significant accuracy in the ANFIS model no. 2 when comparison with ANN model no.2 by reducing MSE by (99.99) and increasing R by (58.23%). Also, there is significant accuracy in the ANFIS model no. 3 when comparison with ANN model no.3 by reducing MSE by (77.74%) and increasing R by (5.01%).

Table 4. Results of comparison between ANFIS and ANN computed over the checking period for the first group

Mode no.	Description	MSE	R
1	ANFIS	0.000441	0.999099
	ANN	0.026	0.9164
2	ANFIS	4.41E-06	0.999987
	ANN	0.06	0.632
3	ANFIS	0.001781	0.995529
	ANN	0.008	0.948

In the second group of this study, the recharge rate is added to the input of variable. The input data of these models (4, 5, and 6) includes hydraulic heads and recharge rates and the target variable is hydraulic head only. In the model No.4, the hydraulic heads and recharge rates of November are used as input variables, while, the hydraulic heads of December are used as target variable. The details of inputs (a) and output (b) membership functions parameters values for model no.4 are illustrated in Table 5. Table 6 shows the best value of clustering radius associated with lowest value of chRMSE.

Table 5. Input (a) and output (b) membership functions parameters of model no.4

a			a		
input	H_{Nov}		input	R_{Nov}	
Parameter	σ	μ	Parameter	σ	μ
mf1	0.4613	1.819	mf1	21.6	122.2
mf2	0.4613	2.618	mf2	21.6	122.2
b			b		
output	H_{Dec}				
Parameter	C1		C2	C3	
mf1	0.9642		-8.45e-005	0.07349	
mf2	1.006		0.0002427	-0.006641	

Table 6. Input, target, r, chRMSE, and number of rules of the ANFIS models in the second group.

Model No.	Input (hydraulic head, recharge rate)	Target (hydraulic head)	r	chRMSE	No. of rules
Model No. 4	Nov	Dec	0.5	0.0213	2
Model No. 5	Apr, May, Jun	Jul	0.7	0.0021	3
Model No. 6	Apr, May, Jun, Jul	Aug	0.2	0.0422	8

Table 7 shows the comparison between the current study and the study that conducted by using ANN for the second group. There is no significant increase in the estimation accuracy when adding another input variable (recharge rate). Because the amount of this variable is very little, so its influence on the results was imperceptible. It can be concluded that the ANFIS models are superior to the ANN models. There is a significant improvement in the models performance when comparison with models of ANN, by reducing MSE by (97.6%) and increasing R by (5.17%) for model no.4. Also, for ANFIS model no. 5 when comparison with ANN model no.5 by reducing MSE by (99.99%) and increasing R by (53.14%). The accuracy results of the ANFIS model no. 6 is better when comparison with ANN model no.6 by reducing MSE by (78.54%) and increasing R by (2.64%).

Table 7. The results of comparison between ANFIS and ANN computed over the checking period for the second group

Mode	Description	MSE	R
4	ANFIS	0.000454	0.999159
	ANN	0.0189	0.95
5	ANFIS	4.41E-06	0.999987
	ANN	0.067	0.653
6	ANFIS	0.001781	0.995575
	ANN	0.0083	0.97

From the results of comparison between ANN and ANFIS, the ANFIS models perform better than the ANN models in the checking phase. The main reason is that the ANFIS model integrates both neural networks and fuzzy logic principles; thus it has the ability to draw the benefits of both in a single frame. Therefore, the ANFIS model appears to be more appropriate than the ANN model for the process of establishing a rating relationship between input data and the groundwater head. Figure 3 through 8 show scatter plot between MODFLOW (calculated head) and ANFIS models (calculated head) for the first and second group.

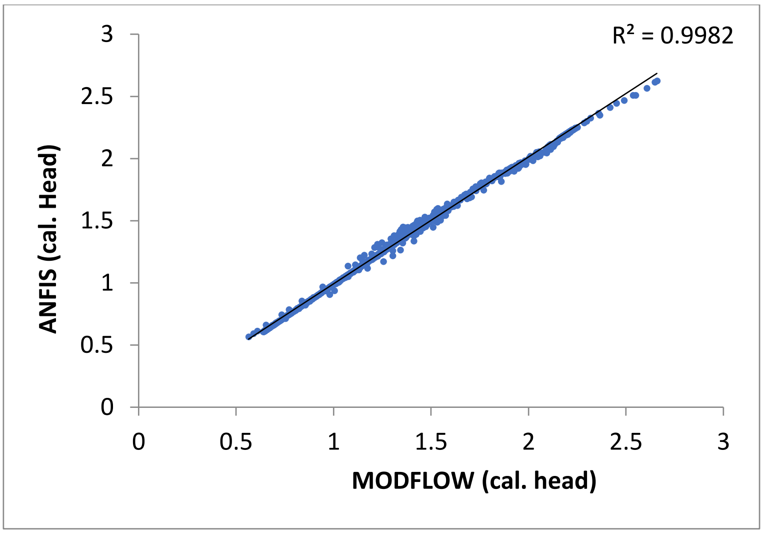

Figure 3. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.1

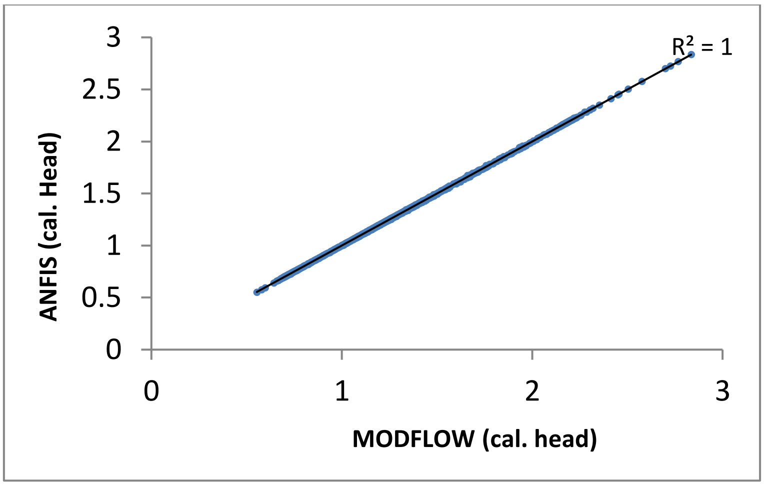

Figure 4. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.2

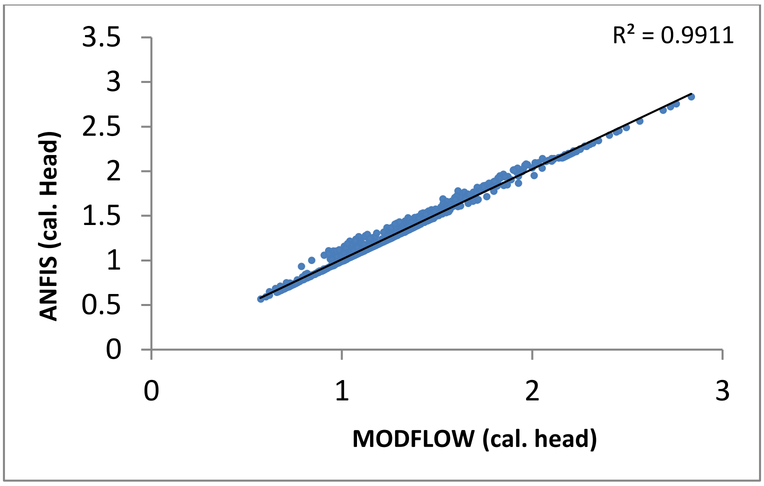

Figure 5. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.3

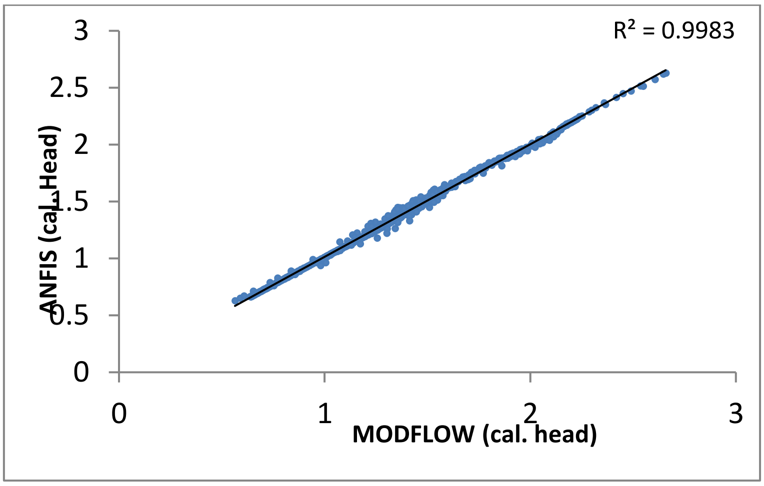

Figure 6. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.4

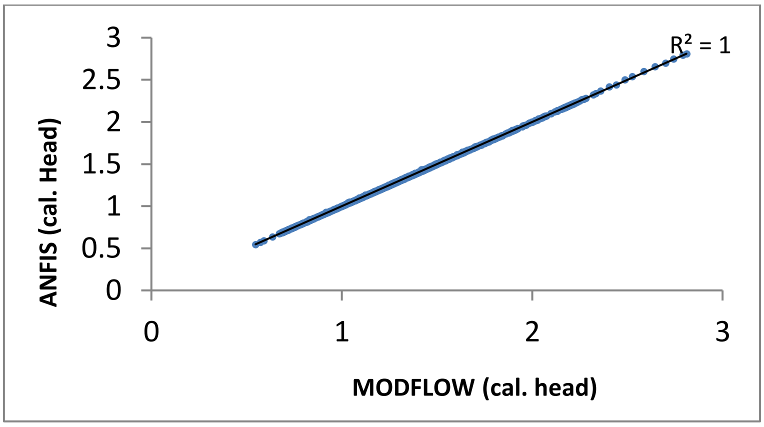

Figure 7. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.5

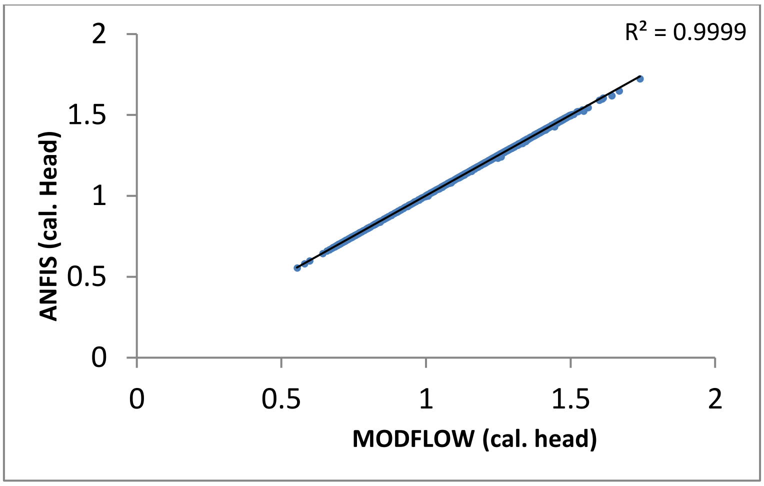

Figure 8. Scatter plot between MODFLOW (cal. head) and ANFIS (cal. Head) for model no.6

5. Conclusions

A finite difference two-dimensional model is used for modeling the groundwater flow for the upper aquifer in the study area; the calibrated values of hydraulic conductivity vary over the range (15-150) m/day. While, the calibrated values of specific yield vary over the range (0.125-0.45). The input data for constructed ANFIS models was generated using the calibrated MODFLOW model (V5.33). MODFLOW model generates (3797) hydraulic head values during each month. 70% of these values (2658 samples) was used in training phase, the remaining values (1139 samples) was used in checking phase. Two groups of ANFIS models were built to predict the groundwater heads and the compared with other study that conducted by ANN. The first group has only one input variable (hydraulic head). The second group has two input variables (hydraulic head and recharge). There is a significant improvement in the ANFIS models performance when comparison with models of ANN. There is no significant increase in the estimation accuracy when adding another input variable (recharge rate). Because the amount of this variable is very little, so its influence on the results was imperceptible. It can be concluded that the ANFIS models are superior to the ANN models. The ANFIS model seems to be more suitable than the ANN model for the process of groundwater head prediction.

CONFLICT OF INTERESTS.

- There are no conflicts of interest.

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دراسة مقارنة لنظام الاستدلال العصبي الضبابي المكيف والشبكات العصبية الاصطناعية للتنبؤ بالمنسوب الهيدروليكي للمياه الجوفية في منطقة قاحلة

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الخلاصة

يهدف هذا البحث إلى تطوير نموذج تنبؤي لتقدير منسوب المياه الجوفية في منطقة سفوان–الزبير باستخدام نظام الاستدلال العصبي الضبابي المكيف (ANFIS). تمثل هذه المنطقة الجزء الجنوبي من الصحراء العراقية، وهي منطقة قاحلة ذات موارد مائية محدودة. تم توليد البيانات المطلوبة لبناء نموذج ANFIS باستخدام نموذج (MODFLOW V.5.3). حيث تمت معايرة نموذج MODFLOW اعتمادا على القياسات الحقلية خلال سنة واحدة. ولد نموذج MODFLOW (3797) قيمة للمنسوب الهيدروليكي خلال كل شهر. استخدمت 70 ٪ من هذه القيم (2658 عينة) للتدريب، و30 ٪ منها (1139 عينة) في عملية التحقق. تم مقارنة دقة نماذج ANFIS مع دراسة سابقة معتمدة على تقنية الشبكة العصبية الاصطناعية (ANN). كانت متغيرات الادخال من المناسيب الهيدروليكية المتعاقبة ومعدلات تغذية المياه الجوفية. لا توجد زيادة كبيرة في دقة التقدير عند إضافة متغير إدخال آخر (معدل تغذية المياه الجوفية)، لأن مقدار هذا المتغير قليل جدًا، لذلك كان تأثيره على النتائج غير محسوس. توضح مقارنة ANFIS وANN أن نموذج ANFIS هو أفضل من ANN في مرحلة التحقق. يمكن ان يعزا ذلك الى ان نموذج ANFIS يجمع بين أساسيات المنطق الضبابي والشبكات العصبية؛ وبالتالي يمكن استخدام خصائصها في إطار واحد. يمكن استنتاج أن نموذج ANFIS أكثر ملائمة من نموذج ANN للتنبؤ بالمنسوب الهيدروليكي للمياه الجوفية من بيانات المدخلات ذات الصلة.

الكلمات الدالة: ANFIS؛ ANN، النمذجة العددية؛ هيدروليكية المياه الجوفية، العراق