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Well Field Design in a Highly Fractured Aquifer System : A Case Study of the Egypt's Siwa Oasis

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Abstract: In highly fractured aquifer systems, simulation of groundwater flow using the well known classical approaches such as numerical and analytical models is practically impossible in most cases. Recent advances in research in the area of model identification have revealed approaches for inducing models from data, based on learning systems. These approaches can determine the relationships between the input and output variables from data presented to them, without resorting to describing these relationships explicitly in mathematical form. The design of the free flowing groundwater well fields in such aquifer system requires the determination of the free flowing rate and the separation distance between the wells to avoid any undesirable interference. The artificial neural network approach as a model induction from data was used to estimate these two variables in the aquifer system of Egypt's Siwa Oasis, which is characterized by its high fracture intensity and the wide variation of the fracture apertures. Combined with already available understanding of the physical process, the developed model results showed consistency with the observed data to a high degree of confidence. This study is intended to assist the decision makers dealing with groundwater resource management in such complicated system.

Key words: Fractured aquifer • Neural network • Mathematical form • Physical process

INTRODUCTION

In highly fractured rocks, the analysis of ground flow is normally carried out with the continuum approach, which involves the replacement of the fractured media, by a representative continuum. The continuum approach is valid as long as the fracture spacing is sufficiently dense where the fractured media acts in a hydraulically similar fashion to granular porous media. With this valid assumption, there are still some limitations when applying the classical groundwater flow models due to the non-Darcian flow behavior in fracture aquifers with wide aperture. In addition, the spatial variability of the fractures hydraulic properties is always of concern and hard to estimate. In cases where the fracture spacing is irregular in a given direction, the media will exhibit trending heterogeneity. Also, if the fracture spacing is different in one direction than they are in another, the media will exhibit anisotropy.

The utilized carbonate aquifer system in the Siwa Oasis, which is located in the Northern part of the Western Desert of Egypt, is characterized by its high fracture intensity and the wide variation of the fracture apertures. In spite of the small distance between the existing free flowing wells, it was found that there is significant variation in both water quality and quantity. To evaluate the groundwater resources in the highly fractured aquifer system of the Siwa oasis, the groundwater system can be treated as a porous media. This assumption is valid only on the regional scale of the oasis but could not answer specific questions related to the point wise spatial variation of the aquifer potential and the minimum distance required between any two wells to avoid undesirable well interference.

Empirical models, which are capable of identifying a direct mapping between the inputs and outputs, are used in order to avoid the computational burden imposed by complex, process-based models. Due to gross simplification, inadequate calibration and system noise etc, such models do not always perform particularly well. Recently, significant progress in the realm of non-linear pattern recognition has been made possible through advances in a modeling of artificial neural networks (ANNs).

Artificial neural network technique is widely used to solve variety of complex scientific and engineering

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problems. It is a computing system made up of simple interconnected elements, which are arranged to simulate neurons in biological systems in human beings. It is a non-linear mapping system, whose structure is loosely based on principle observed in the nervous system [1]. It has the capability of learning relationships between the inputs and outputs without any prior knowledge of relationships between them. Using the ANNs technique, the computer learns to make intelligent decision using known input and output data and adjusts some internal parameters of the network through repetitive introduction of known examples.

ANNs are suited to complex problems, where the relationships between the variables to be modeled are not well understood. This is because they belong to the class of data-driven approaches that have the ability to determine which model inputs are critical [2], so there is no need for "a priori rationalization about relationships between variables" [3]. The data requirements for ANN models are usually less. In many instances, data collection programs need to be carried out to adequately calibrate physically based models, which is both time consuming and costly. In addition, complete data sets are required for physically based models to function.

The objective of this paper is to apply the Artificial Neural Networks on a pilot area in Siwa Oasis to examine the correlation among the existing wells producing from the highly fractured aquifer system, to develop a relationship, which will describe the spatial variation of the free flowing discharge rates and to identify the minimum distance between wells to avoid any undesired interference.

MATERIALS AND METHODS

Description of the Study Area: The Siwa depression is an isolated closed basin located in the northern part of the Western Desert of Egypt, about 65 kilometers east of the Libyan border and 300 kilometers south of the Mediterranean Sea as shown in Figure (1). Geologically, the carbonate aquifer system is predominantly hard limestone with chalky limestone in some localities.

This change in the aquifer faces leads to a possible change in the water quality. The chemical analysis of the water samples showed that the total dissolved solids vary between 1500 and 7500 ppm.

Ancient writers reported that Siwa once contained thousands of naturally flowing springs. In 1963 there were less than 200 developed springs of any importance with a maximum depth of 12 meters [4]. In 1981, farmers invented their own drilling machine that enabled them to drill thousands of poorly designed wells in the fractured limestone aquifer.

This irresponsible action led to a surplus of water supply. As a result of the excess groundwater flow, the drainage basins became inefficient to accept the water losses from the wells and farmers started to complain of loosing their cultivated lands caused by water logging and soil salinization problems.

In 1996, the Government of Egypt responded to this vital socio-economic issue and launched a research project to investigate and identify the problems and to propose short and long-term mitigation options.

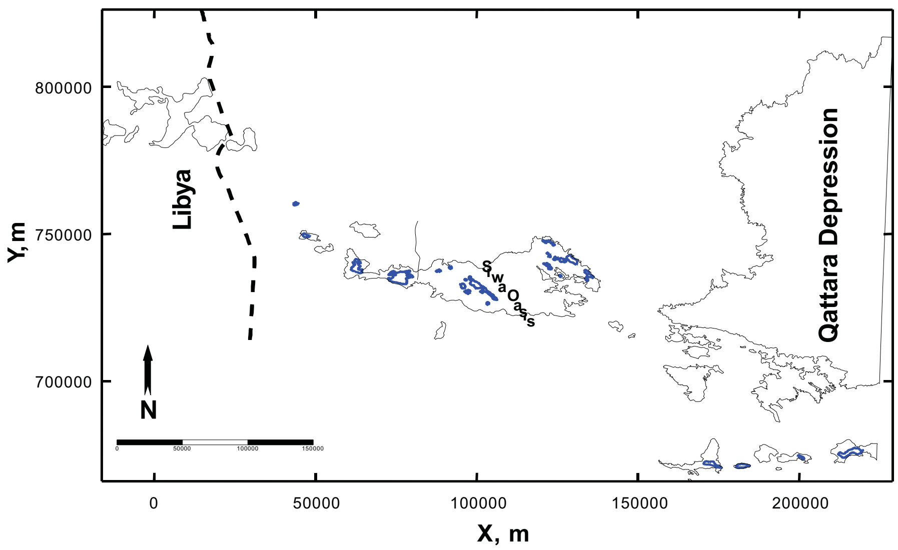

Fig. 1: Location map of the study area

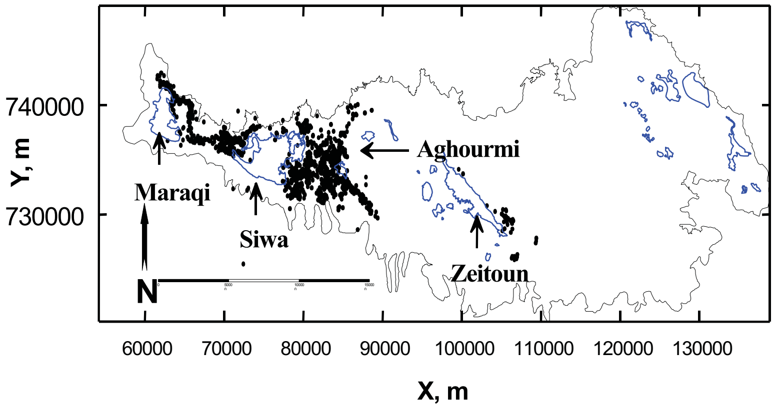

Fig. 2: Well location map for Siwa Oasi

Table 1: Distribution of the free flowing discharge from the existing wells and springs

Catchment Area	Total free flowing rate m^3/day
Maraqi	60,000
Siwa	140,000
Aghourmi	120,000
Zeitoun	80,000

The field investigation conducted by the Research Institute for Ground Water [5] included the exact location of the wells and the springs, ground surface elevation, well depth, flow rate measurements, complete chemical analysis and the cultivated area served by each well and spring.

Figure (2) shows the spatial distribution of these wells and springs. The existing wells are shallow in depth and range from 10 meters for the natural springs to 120 meters for the hand-dug wells.

All these shallow wells are poorly designed with no casing or control valves. The well inventory showed that 400,000 m^3/day were flowing continuously and only 42 % of this water was used for irrigation and the rest was diverted to the poor drainage network forming hyper saline lakes. As presented in Figure (2), the discharge rate from the flowing wells and springs varies from 0.5 to 80 m^3/hr and distributed among the four catchments as classified in Table (1).

The data analysis showed that a rehabilitation program to control the groundwater flow from the poorly designed hand dug wells is a must and considered as the only solution to preserve the oasis and conserve the groundwater resources to fulfill the future demands. This program is simply aiming at terminating the old wells and drilling new properly designed wells. It is worth mentioning that the natural flowing springs are not included in the control program and left as an attractive tourist feature. Also, there should be a minimum continuous flow rate to the lake to maintain the lake wet around the year to avoid any environmental implications.

Model Induction from Data: Recent advances in research in the area of model identification have revealed approaches for inducing models from data, based on learning systems. These approaches can determine the relationships between the input and output variables from data presented to them, without resorting to describing these relationships explicitly in mathematical form. One such learning system, which is the subject of this study, is that of artificial neural networks. The neural network is a system of processing units with simple multiplicative, additive and other functional elements that are connected into a network through a set of weight such that this network provides a relationship between the input and output data sets. The mode of functioning of the network is determined by the network's architecture, the magnitudes of the weights and the mode of operation of the processing elements.

Artificial Neural Networks-based model was used to describe the spatial distribution of well flowing rates with horizontal variations. The variance provides an incomplete description of the variability, as there is no relationship between it and the distance between the observations. ANN-based model offers an alternative approach with quantified spatial prediction with interdependence of flowing rates. To identify the spatial variation structure in the present study, the correlation among the existing wells producing from the highly fractured aquifer was based on the relationship between the root mean square error and the distance between well pairs.

A back-propagation ANNs theory provides a general adaptive model for learning an arbitrary mapping from an input space to an output space. This mapping function is fulfilled by simulating a neural network topology, presenting it with a series of training samples and applying the back-propagation learning rule. Through the learning rule, the network adapts and learns from the training set examples to respond correctly to its environment [6].

The ANN model is composed of layers of simple information-processing neurons (nodes). The output of node j is given by

$$\text{yi} = f\left(\sum a_i w_{ji} + b_j\right)$$

Where a_i is the output of node i in the preceding layer, w_{ji} is the connection weight between nodes j and i and b_j is the bias term of node j responsible for accommodating nonzero offsets in the data. The node's input-output transformation function, f, has the following form with an output value from 0 to 1:

$$f(\text{x}) = 1/\left(1 + \exp(-\text{x})\right)$$

In this application, a minimum three-layer feed-forward ANN model was constructed. The network's output layer represented the free flowing rate of the target wells and the input layer represented the flowing rates of other wells surrounding the target ones and their corresponding separation distances. During the network's learning process, a series of input patterns with their corresponding expected output values were presented to the network and the connection weights between nodes of different layers were adjusted by back-propagation algorithm with the momentum term. The objective function used for optimization was the Root Mean Squared Error $(\text{RMSE})_{\text{ANN}}$ defined as:

$$(\text{RMSE})_{\text{ANN}} = \left(\frac{1}{n}\sum_{s=1}^{n}\left[\sum_{k=4}^{m}(t_{sk} - y_{sk})^2\right]\right)^{0.5}$$

Where t_{sk} is the expected output, y_{sk} is the predicted output, m is the number of output nodes and n is the number of training set samples. To avoid the network's over fitting, a validation set obtained in a fashion similar to the training set was used to monitor the network's well-trained point. When the $(\text{RMSE})_{\text{ANN}}$ error for the validation set reached a minimum value, the training process was stopped.

According to the generalized δ rule [6], the δ error term at output node k for training set sample s is expressed as:

$$\delta_{sk} = (t_{sk} - y_{sk})\, y_{sk}\, (1 - y_{sk})$$

While the δ error term at hidden node j for training set, sample s is expressed as:

$$\delta_{sj} = y_{sj}(1 - y_{sj})\left(\sum \delta_{sk} w_{kj}\right)$$

Where y_{sj} is output of hidden node j and w_{kj} is the connection weight between output node k and hidden node j.

The basic of the latter equation is to propagate the δ error terms produced in the output layer backwards one layer through the network system. A similar procedure is recursively applied until the input layer is reached. Then these δ error terms are used to adjust the connection weights:

$$\Delta w_{ji}(q) = \in \delta_{sj} y_{si} + a \Delta w_{ji}(q-1)$$

where $\Delta` w_{ji}$ is the change value in the connection weight between hidden node j and input node i, q and (q-1) refer to the present and previous cycles of training set, respectively, . is the learning rate and α is the momentum term, which is used to filter out high-frequency fluctuations of the network and to prevent to some extent the convergence process from getting trapped into the local minima. The output of input node i for training set sample s, y_{si} was directly set to the input signal of node i without any transformation in the present application. A similar equation is used to adjust the connection weight between output node k and hidden node j and in this case, the δ error term at output node k, δ_{sk} is used.

RESULTS AND DISCUSSION

The spatial distribution of the new wells (66 wells) that were used in the analysis is shown in Figure (3). Wells located on the other sides of the lakes were not included in the analysis to guarantee the continuity of the data. The free flowing discharge from the new wells varies between 10 to 360 m^3/hr. The values of the flow rates are very high compared to the old wells due to the full penetration of the new wells into the productive fractures and due to the use of the steel casings that prevent water losses to the unproductive fractures.

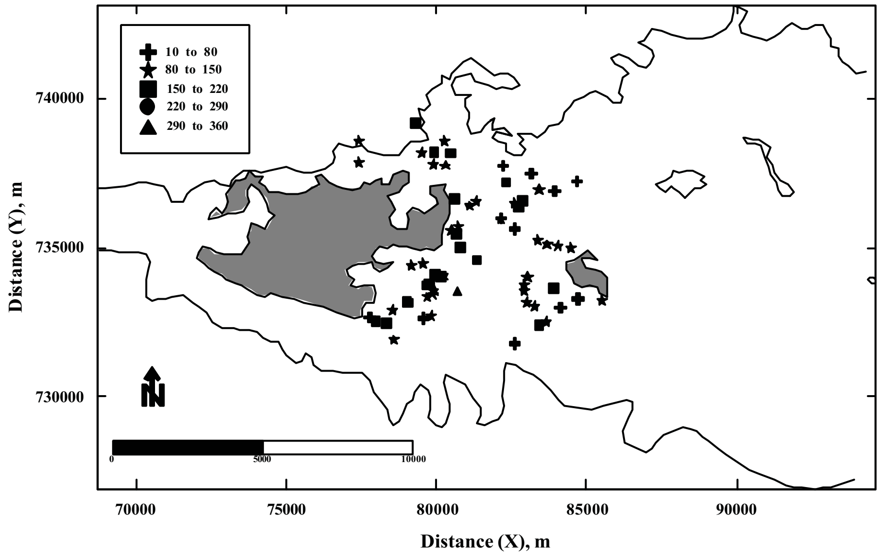

Fig. 3: Spatial distribution of the new wells, based on flow rate Q (m^3/hr)

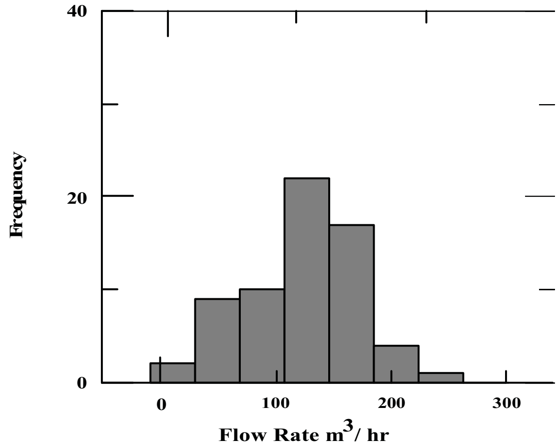

Fig. 4: Untransformed frequency distribution of discharge rates from the new wells

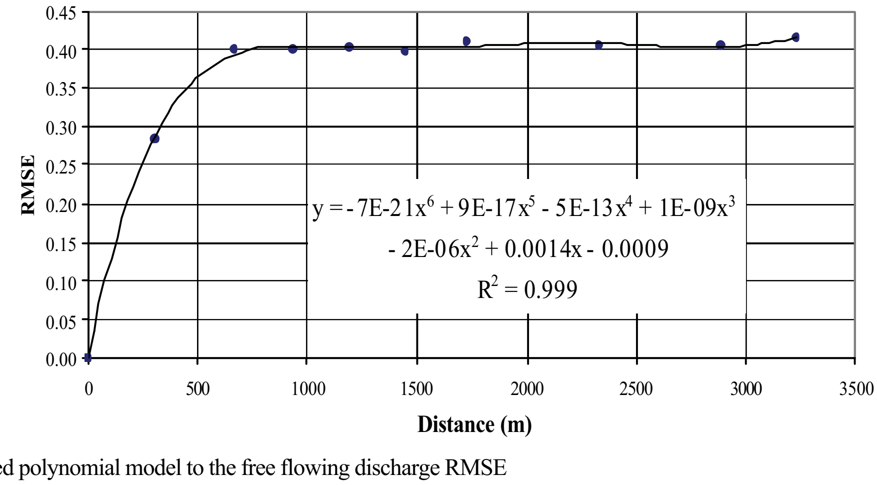

Fig. 5: Fitted polynomial model to the free flowing discharge RMSE

Figure (4) shows the frequency distribution of the free flowing discharge rate for the untransformed data. The χ^2test proved that the discharge rate fits a normal distribution function and can be depicted easily from the figure. The mean values for the flow rates are 125 m^3/hr and the sample standard deviation is 56. The coefficient of variation, which is defined as the standard deviation divided by the mean, is equal to 45%.

In order to produce successful predictions with the minimum amount of error and training time, the optimization technology of genetic algorithm was used as modeling of a selective evolutionary process, which develops superior entities from a population of entities. The genetic algorithm used in the developed model attempts to select the best subset of data from that provided as input, configure the best neural network that will train with the data and adjust the various parameters that control the neural network to optimum points. To examine the correlation among the existing wells producing from the highly fractured aquifer system, it was necessary to identify the spatial variation structure based on the distance between sample pairs and root mean square error (RMSE) as described by:

$$\mathrm{RMSE} = \left(\sum_{i=1}^{n} (O_i - P_i)^2 N^{-1} \right)^{0.5} O_m^{-1}$$

Where O_i is the measured well flow rates, P is the predicted output, N is the number of wells and O_m is the mean value of O_i. The RMSE values show that the predictions overestimate or underestimate the measurements by 0.283% to 0.415% of the mean value of the measurements. The polynomial regression is used to fit the spatial changes in the free flowing discharge with sixth degree equation as shown in Figure (5). The minimum spatial changes of RMSE are started from a separation distance of 900 meters (as calculated by polynomial model with multiple R of o.999). This is in close agreement with the field observation from the pumping test that proved the distance between wells should not be less than 1000 meters to avoid any undesirable interference.

To estimate the free flowing discharge rates that describe the aquifer potential at any particular point, the efficiency of the ANN model is described by the index of agreement (d):

$$d = 1 - \left[\sum_{i-1}^{N} \left(P_1 - O_i \right)^2 / \sum_{i-1}^{N} \left(|P| + |O| \right)^2 \right], 0 \le d \le 1$$

Where P = P_i - O_m and O = O_i - O_m . The d-values close to 1 show that the model is in good agreement with the observed values. The index is intended to be a descriptive measure and it is both a relative and bounded measure, which can be widely applied in order to make cross-comparisons between models [7]. Compared with the measured free flowing discharges in the study area, the model produced reliable results in terms of separation distances where the ANN-based model efficiency appears valid over the index of agreement values ranged from 0.58 to 0.79. This confirms the potential of the used approach of model induction from data aims at providing tools to facilitate the conversion of data into other forms that provide better ways of simulating the physical processes that generated these data. When combined with already available understanding of the physical process, this new application, result in an improved formulation of modeling problems and so provide an improved capability. The valid model was applied to estimate the flow rate at the unsampled locations. Along with the available data set values, the model was used to provide unbiased estimate using the structural properties of the artificial neural network approach developed earlier. Figure (6) shows the spatial distribution of the free flowing rates as estimated using the artificial neural network. This map can be considered directly by the decision making to manage the aquifer system in the study area. Therefore, it can be useful tool in regulating the well licensing system to identify locations where groundwater is suitable for agriculture. The work presented in this study demonstrates the ANN approach as one possible direction of progress towards the next generation of groundwater models and applications.

CONCLUSION

Based on learning systems, the approach for inducing models from data demonstrated the capacity of the artificial neural networks modeling as a useful tool to determine the aquifer potential based on the flow rates in highly fractured aquifer systems. Using the back-propagation learning rule, the developed ANN model performed satisfactorily for the flow rate spatial prediction at the unsampled locations (index of agreement = 0.58-0.79). For the free flowing discharge from the wells, it was found that spatial correlation between the wells exists for a distance less than 900 meters. This result, which closely matches the pumping test analysis conducted in the study area, provide valuable information to the decision makers. This paper is intended to assist those authorities involved in the design of groundwater well fields as well as the decision makers with groundwater resource management in such complicated system.

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