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Predicting the Impact of Subsurface heterogeneous Hydraulic Conductivity on the Stochastic Behavior of Well Draw down in a Confined Aquifer Using Artificial Neural Networks

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Groundwater flow and behavior have to be investigated based on heterogeneous subsurface formation since the homogeneity assumption of this formation is not valid. Over the past twenty years, stochastic approach and Monte Carlo technique have been utilized very efficiently to understand the groundwater flow behavior. However, these techniques require lots of computational and numerical efforts according to the various researchers' comments. Therefore, utilizing new techniques with much less computational efforts such as Artificial Neural Network (ANN) in the prediction of the stochastic behavior for the groundwater based on heterogeneous subsurface formation is highly appreciated. The current paper introduces the ANN technique to investigate and predict the stochastic behavior of a well draw down in a confined aquifer based on subsurface heterogeneous hydraulic conductivity. Several ANN models are developed in this research to predict the unsteady two dimensional well draw down and its stochastic characteristics in a confined aquifer. The results of this study showed that ANN method with less computational efforts was very efficiently capable of simulating and predicting the stochastic behavior of the well draw down resulted from the continuous constant pumping in the middle of a confined aquifer with subsurface heterogeneous hydraulic conductivity.

Key Words : Artificial Neural Network, Groundwater, Well Draw Down, Stochastic, Heterogeneous Subsurface Formation

1. Introduction

Investigating the groundwater behavior cannot be performed using the homogeneous subsurface assumption. Therefore, the utilization of the subsurface heterogeneity in understanding the groundwater flow behavior in any field application is necessary. Numerical and analytical stochastic approaches have been widely used to accurately simulate the groundwater flow behavior.

Pumping water using a deep groundwater well from a confined aquifer is considered one of the most common groundwater field applications. Understanding the unsteady well draw down spatially based on heterogeneous subsurface formation is very necessary for the field engineer in designing the well safe pumping rate to avoid draining the aquifer. Several researches have been directed mainly towards the investigation of the ground water flow and its characteristics during the pumping process. Due to space limitation, only the recent ones will be considered in this text. Indelman et al. (1996) presented a first-order sensitivity analysis of draw down prediction considering the uncertainty in estimating the hydrau-

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lic properties of multiple leaky aquifer systems. In this study, a new set of dimensionless parameters was suggested to reduce the amount of sensitivity coefficient calculations. On the other hand, Oliver (1998) presented a study to investigate the influence of nonuniform transmissivity and storativity on draw down. The author used the perturbation approach to derive the Frechet derivatives and kernels for the effect of two-dimensional areal variations in transmissivity and storativity on draw down at an observation well. The study showed that observation well draw down is relatively sensitive to near-well transmissivity variation, especially if the nonuniformity was not radially symmetric around the well. Abdin and Abdeen (1999) presented a study to investigate the impact of subsurface heterogeneous hydraulic conductivity on the unsteady two-dimensional pumping well draw down in a confined aquifer. The authors in this study utilized the well-known Monte Carlo technique to evaluate the variability of the unsteady draw down as a result from several variable heterogeneous hydraulic conductivity realizations. The results of this study showed the importance of considering the variability in subsurface hydraulic conductivity in designing the pumping rate from a confined aquifer well and how the well draw down was very much affected by changing the subsurface properties. Different from the stochastic approach, Gebremariam (2002) presented a Phd study for the determination of aquifer parameters using pumping test data. The author stated that the data collected in the field by pumping test should be analyzed by producing standard graphs manually to match with or by using some computer softwares. The author utilized the Aquifer Test software version 3 to process pumping test data with aim of estimating aquifer properties such as hydraulic conductivity and storativity. He finally calibrated his estimated parameters by performing comparison between the measured and the calculated ground water potentials using Visual Modflow software. Recently and back to stochastic approach, Chan and Govindaraju (2003) developed a new mathematical model for the subsurface hydraulic properties (specifically the soil water retention curve and the relative hydraulic conductivity curve) by conceptualizing the soil as a random assemblage of soil particles represented by randomly sized overlapping spheres (fully penetrable spheres). The authors assumed that the spatial arrangement of the spheres was following a homogeneous Poisson process. They performed stochastic analysis to obtain analytical expressions for soil water retention curves and relative conductivity at varying water contents. A quantitative evaluation of the authors' new model was performed by examining data on hydraulic properties for several soils and comparisons with currently used expressions such as Van Genuchten, Brooks-Corey, and Kosugi models. The results of this study showed that the new developed model provided reasonable fits with the observed water retention curve and good predictions of the hydraulic conductivity particularly for soils exhibiting a distinct air entry pressure.

It is quit clear from the literature mentioned previously the amount of numerical effort required to accurately investigate and understand the groundwater well draw down using the stochastic approach. This fact urged the need for utilizing new technology and techniques to facilitate these comprehensive numerical computations and at the same time preserving high accuracy.

Artificial intelligence has proven its capability in simulating and predicting the behavior of the different physical phenomena in most of the engineering fields. Tahk and Shin (2002) presented a study on the fault diagnosis of Roller-Shape using frequency analysis of tension signals and Artificial Neural Networks (ANN) based approach in a web transport system. Specifically, the authors suggested a new diagnosis algorithm to detect the effective rollers based on the frequency analysis of web tension signals. Throughout their study, the authors utilized the characteristics features of tension signals (RMS, Peak value, and Power spectral density) to train an ANN that classified the roller condition into three groups (normal, warning, and faulty conditions). The results of this study showed that the suggested diagnosis algorithm could be successfully used to identify the effective rollers as well as to diagnose the degree of the defect of those rollers. Park and Seo (2003) explored a new Life Cycle Assessment (LCA) methodology for the product concepts by grouping products according to their environmental characteristics and by mapping product attributes into environmental impact driver (EID) index. The relationship is statistically verified by investigating the correlation between total impact indicator and energy impact category. Thereafter, the authors developed an ANN model with back propagation to predict an approximate LCA of grouping products in conceptual design. The results of the ANN model were compared with those of multiple regression analysis. Finally the authors stated that the proposed approach did not replace the full LCA but it would give some useful guidelines for the design of environmentally conscious products in conceptual design phase.

Regarding civil engineering, in general, and water engineering field area specifically, ANN is considered one of the artificial intelligence techniques that have been widely utilized. Several researchers have incorporated ANN technique in hydrology, groundwater, hydraulics, and reservoir operations to simulate their problems. Solomatine and Toorres (1996) presented a study of using ANN in the optimization loop for the hydrodynamic modeling of reservoir operation in Venezuela. The authors stated that the ANN representation of the hydrodynamic/hydrologic model could easily allow the incorporation of the various modeling components into the optimization routines. Minns (1996) investigated the general application of ANN in modeling rainfall runoff process. The results of the numerical experiments reported in his study indicated that ANN was capable of identifying usable relationships between runoff discharges and antecedent rainfall depts. Ramanitharan and Li (1996) utilized ANN with back-propagation algorithm for modeling ocean waves that were represented by wave height and period. This study showed the applicability of forecasting the ocean waves with different neural networks for wave height and period. Tawfik et al.(1997) showed the applicability of using the ANN technique for modeling rating curves with hysteresis sensitive criterion. Kheireldin (1998) presented a study to model the hydraulic characteristics of severe contractions in open channels using ANN technique. The successful results of his study showed the applicability of using the ANN approach in determining relationship between different parameters with multiple input/output problems. Abdeen (2001) developed a neural network model for predicting flow characteristics in irregular open channels. The developed model proved that ANN technique was capable with small computational effort and high accuracy of predicting flow depths and average flow velocities along the channel reach when the geometrical properties of the channel cross sections were measured or vice versa. Chandramouli and Raman (2001) developed a dynamic programming-based neural network model for optimal multi-reservoir operation. In this developed model, the multi-reservoir operating rules were derived using a feed-forward neural network from the results of three state variables' dynamic programming algorithm. The authors applied the multi-reservoir system called Parambikulam Aliyar Project in their study. Comparison between the developed model against first the regression-based approach used for deriving the multi-reservoir operating rules from optimization results ; and second the single-reservoir dynamic programming-neural network model approach showed an improved operating performance. Hsu et al.(2002) presented a multivariate ANN procedure entitled self-organizing linear output map (SOLO) whose structure was designed for rapid, precise, and inexpensive estimation of network structure/parameters and system outputs. Specifically, the authors commented that SOLO provides features that facilitate insight into the underlying processes, thereby extending its usefulness beyond forecast applications as a tool for scientific investigations. These characteristics were demonstrated in their paper using a classic rainfall-runoff forecasting problem. In addition, the authors have tested the various aspects of their model performance using comparison with other commonly used modeling approaches including multilayer feed-forward ANNs, linear time series modeling, and conceptual rainfall-runoff modeling.

It is quit clear from the previously presented literature that ANN technique showed its applicability in simulating and predicting the behavior of different engineering and hydrologic problems. However, the utilization of ANN technique in simulating and predicting the stochastic behavior of the groundwater flow based on heterogeneous subsurface formation and especially the stochastic fluctuation and characteristics of unsteady well draw down is very limited. Therefore, the presented study is aimed towards utilizing the ANN technique in modeling the two-dimensional stochastic behavior of the unsteady well draw down resulted from pumping water from a confined aquifer.

2. Problem Description

The current paper simulates and predicts the stochastic behavior of the two-dimensional unsteady well draw based on heterogeneous subsurface formation using ANN technique. A full penetrating well that is discharging water from a confined aquifer is considered as shown in Figure 1. The aquifer thickness is assumed to be 100.0 m. The data used in the current study is the one presented by Abdin and Abdeen (1999) where they utilized the Monte Carlo approach to simulate the stochastic behavior of the well draw down and they strongly commented about the tremendous and extensive numerical efforts performed in their study. In addition, Monte Carlo approach adopted in Abdin and Abdeen (1999) was used

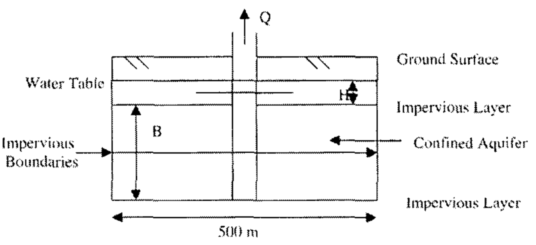

Fig. 1 Schematic diagram for the investigated problem

for simulating the stochastic behavior of the well draw down based on existing and determined subsurface heterogeneous formations. As it is very well known and commented by many researchers, Monte Carlo technique involves huge computational efforts in its application. The reader is kindly referred to the study presented by Abdin and Abdeen (1999) for the complete description of the Monte Carlo approach and its associate mathematical computations and results.

However, the current presented study utilized ANN technique in developing an easy, but numerically efficient, model for simulating this stochastic behavior based on some existing determined data and thereafter the model is used for predicting this behavior for unknown subsurface heterogeneous formations. This is considered the added value of the current paper which is presenting a simple computational modeling approach for the prediction of the stochastic behavior of the well draw down based on limited heterogeneous subsurface formation with small computational effort.

Specifically, several neural network models are developed in this study to accurately imulate the highly heterogeneous and stochastic unsteady well draw down fluctuations. The subsurface heterogeneity in this study is represented by the two-dimensional stochastically generated hydraulic conductivity as they were presented in Abdin and Abdeen (1999). The mathematical and hydrologic parameters of the investigated problem can be shown in Table 1 as they were reported by Abdin and Abdeen (1999). On the other hand, if field data were available for the same problem, the ANN approach and its methodology, described in this study, can be utilized to simulate this real case.

2.1 Subsurface heterogeneity

The subsurface heterogeneity, in the current study, is presented by the spatially correlated stochastic input process f ; where $f = \ln k$; and k is the hydraulic conductivity. As mentioned by Abdin and Abdeen (1999), several assumptions were used in the generation of this stochastic process and they can be outlined as follows:

Table 1 Mathematical and hydrologic parameters for the investigated application

Parameter	Definition	Value
NX	No. of nodes in the X-direction	50
NY	No. of nodes in the Y-direction	50
DX	Increment spacing in the X-direction	10.0 (m)
DY	Increment spacing in the Y-direction	10.0 (m)
LX	Correlation length in the X-direction	30.0 (m)
LY	Correlation length in the y-direction	30.0 (m)
Ho	Initial water head in the aquifer	10.0 (m)
S	Confined aquifer storitivity	0.002
B	Confined aquifer thickness	100.0 (m)
K	Average Hydraulic conductivity	3.0 (m/day)
Q	Well pumping rate	300 (m^3/day)

(1) Log-hydraulic conductivity ($f = \ln k$) is considered second-order stationary stochastic process, and is assumed to be normally distributed (Chang et al., 1995a and 1995b).

(2) The fluctuations of this process is assumed to have correlation scales smaller than the scale of the flow domain.

(3) The spatial structure of the fluctuations of $\ln K$ will be described by the exponential autocovariance function (Yeh et al. 1985a)

The assumptions listed above have been traditionally used in most previous stochastic analyses of saturated, unsaturated, and multiphase flow. In the Abdin and Abdeen (1999) study, they used the exponential autocovariance function, R_{ff}, and its correspondence spectrum, S_{ff} : as were used by Chang et al., 1995a and 1995b for the two- and three-dimension cases and they can be presented as follows:

$$R_{ff}(\xi) = \sigma_f^2 \exp[-\xi/\lambda] \tag{1}$$

$$s_{ff}(K) = \frac{\sigma_f^2 \lambda^3}{\pi_2 (1+\lambda^2 K^2)^2} \tag{2}$$

where ξ=separation distance, λ=covariance length, σ_f=standard deviation of f, and K= wave number. The random generation of the process is performed using the turning bands method and spectral approach described by Mantoglou and Wilson (1982).

2.2 Stochastic behavior of the well draw down

The study presented by Abdin and Abdeen (1999) investigated the stochastic behavior of the well draw down using the Monte Carlo approach utilizing the input heterogeneous and hydrological data described previously. Specifically Abdin and Abdeen (1999) developed a finite difference-based model for the solution of the two-dimensional unsteady well draw down resulting from a pumping well located in the center of the confined aquifer described in the previous section. Thereafter, the authors utilized the Monte Carlo approach to profoundly investigate the stochastic behavior of the well draw down based on the subsurface heterogeneous formation described above. The authors in Abdin and Abdeen (1999) commented about the huge computational effort required to obtain the main finding stated in their study. This numerous computational process urged the authors to explore new techniques and approaches such as Artificial Neural Networks (ANN) for an easy, but efficient, methodology for simulating and predicting unknown results for the stochastic behavior of the well draw down.

Therefore, the current study presented in this manuscript is mainly concerned with developing an ANN model utilizing part of the input and output data, presented by Abdin and Abdeen (1999), for predicting the stochastic behavior of the well draw down using only the input heterogeneous and hydrological data. For the current study to be complete, the major finding for the stochastic behavior of the well draw down, presented by Abdin and Abdeen (1999), is described.

The main conclusion drawn from Abdin and Abdeen (1999) was the direct impact of the properties of the subsurface heterogeneity to the confined aquifer ground water head variations. The increase in subsurface heterogeneity clearly resulted in a remarkable increase of the unsteady draw down and its variations all over the entire aquifer. On the other hand, the increase in the correlation lengths in both spatial directions did not show a constant (increasing or decreasing) trend for the draw down or its variations all over the entire aquifer. The results, presented in Abdin and Abdeen (1999), clearly recommend the cautious design for the pumping from a well discharging from a heterogeneous confined aquifer so that the aquifer should not be drained.

It is probably worth mentioning here that the current study, presented in this manuscript, does not investigate the stochastic behavior of the well draw down using ANN. However, it develops an ANN model for predicting this stochastic behavior with much less computational effort but efficiently accurate using part of the results presented in Abdin and Abdeen (1999) for training the Neural Networks.

3. Neural Network Structure

Neural networks are models of biological neural structures. Abdeen (2001) described in a very detailed fashion the structure of any neural network. Briefly, the starting point for most networks is a model neuron as shown in Figure 2. This neuron is connected to multiple inputs and produces a single output. Each input is modified by a weighting value (w). The neuron will combine these weighted inputs with reference to a threshold value and an activation function, will determine its output. This behavior follows closely the real neurons work of the human's brain. In the network structure, the input layer is considered a distributor of the signals from the external world while hidden layers are considered to be feature detectors of such signals. On the other hand, the output layer is considered as a collector of the features detected and the producer of the response.

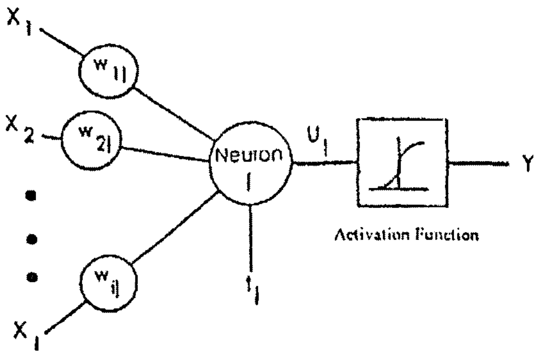

Fig. 2 Typical picture of a model neuron that exists in every neural network

4. Neural Network Operation

It is quit important for the reader to understand how the neural network operates to simulate different physical problems. As described by Abdeen (2001) the output of each neuron is a function of its inputs (X_i). In more details, the output (Y_j) of the j^{th} neuron in any layer is described by two sets of equations as follows :

$$U_j=\sum(X_i w_{ij}) \tag{3}$$

And

$$Y_j=F_{th}(U_j+t_j) \tag{4}$$

For every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th}. This activation function can take several forms but the most commonly used one is the Sigmoid function which has an input to output mapping as shown in Figure 3. The resulting output, Y_j, is an input to the next layer or it is a response of the neural

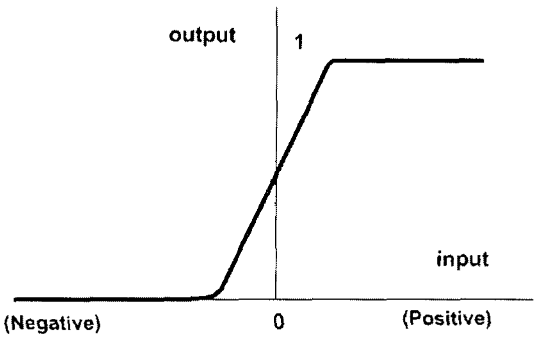

Fig. 3 The sigmoid activation function used in most of the designed networks

network if it is the last layer. On the other hand, other activation functions are commonly used by the researchers in this field such as Step, Linear, Hyperbolic, and Gaussian functions. In applying the Neural Network technique, in this study, Neuralyst Software, Shin (1994), was used.

5. Neural Network Training

The next step in neural network procedure as described by Kheireldin (1998) is the training operation. The main purpose of this operation is to tune up the network to what it should produce as a response. From the difference between the desired response and the actual response, the error is determined and a portion of it is back propagated through the network. At each neuron in the network, the error is used to adjust the weights and the threshold value of this neuron. Consequently, the error in the network will be less for the same inputs at the next iteration. This corrective procedure is applied continuously and repetitively for each set of inputs and corresponding set of outputs. This procedure will decrease the individual or total error in the responses to reach a desired tolerance. Once the network reduces the total error to the satisfied limit, the training process may stop. The error propagation in the network starts at the output layer with the following equations :

$$w_{ij} = w'_{ij} + LR(e_j X_i) \qquad (5)$$

And,

$$e_j = Y_j(1 - Y_j)(d_j - Y_j) \qquad (6)$$

Where, w_{ij} is the corrected weight, w'_{ij} is the previous weight value, LR is the learning rate, e_j is the error term, X_i is the i^{th} input value, Y_j is the ouput, and d_j is the desired output.

6. Simulation Cases

To fully investigate the stochastic behavior of the two-dimensional unsteady well draw down resulted from pumping the water from a confined aquifer with subsurface heterogeneous hydraulic conductivity, several simulation cases are considered in this study. These simulation cases can be divided into two groups. The first group simulates the impact of the subsurface heterogeneous hydraulic conductivity on the two-dimensional unsteady well draw down using ANN. The second group simulates the impact of the same subsurface heterogeneous parameter on the stochastic variability of the two-dimensional unsteady well draw down represented by its standard deviation. Specifically this second group utilizes ANN technique to predict the Monte Carlo results.

7. Neural Network Design

To develop a neural network in order to simulate the impact of the subsurface heterogeneous hydraulic conductivity on the well draw down or its standard deviation (Monte Carlo Case), first input and output variables have to be determined. Input variables are chosen according to the nature of the problem and the type of data that would be collected in the field if this were a field experiment. The basic inputs for the two simulation groups are the one presented in Table 1. These variables are considered to be constant for all the neural network models developed in this study. Besides these basic inputs, other variables are considered to be key inputs for the neural network development of the two simulated groups. To clearly specify the key input variables for each neural network simulation groups and their associated outputs, Table 2 is designed to summarize all neural network key input variables and outputs for these two groups.

Table 2 Key input variables and outputs for the two neural network simulation groups

Groups No.	Simulation case	Input variables		Output Variables
First Group	Unsteady	Time	σ_f	Draw down at the well
	Spatial	X-Distance	σ_f	Draw down after 38 days of continuous pumping
Second Group (Monte Carlo)	Unsteady	Time	σ_f	Standard Deviation of draw down at the well
	Spatial	X-Distance	σ_f	Standard Deviation of Draw down after 38 days of continuous pumping

Where σ_f is the standard deviation of the subsurface heterogeneous hydraulic conductivity.

It can be noticed from Table 2. that each group of neural network simulations consists of two simulation cases (neural network model) for the unsteady and spatial variations of the draw down and its variability. The value of σ_f varies from 0.1 to 1.0 for the first group and from 0.1 to 0.5 for the second group ; and the distance in the x-direction varies from the center of the aquifer where the well is located up to 240.0 m (the aquifer border) for the two groups. On the other hand, each simulation case within each group is divided into two sub-simulation cases. The first one trains the network with the whole domain for σ_f and predicts an intermediate σ_f related outputs (Interpolation prediction). The other sub-simulation case trains the network with limited domain for σ_f and predicts an external σ_f related outputs (Extrapolation prediction). Due to space limitation of the current research paper, the exact numeric values for the inputs and outputs for all the simulation cases will not be listed, however, the reader is referred to the study presented by Abdin and Abdeen (1999) for all these data information.

However, if the ANN model was to be applied to a field experiment, the type of input data needs to be collected would be the same as they are listed in Tables 1 and 2. Similarly, the set of output variables required for the training of the ANN would also need to be collected and reported as they were measured in the field corresponding to their input variables conditions.

Several neural network architectures are designed and tested for each of the sub-simulated cases investigated in this study to finally determine the best network model to simulate, very

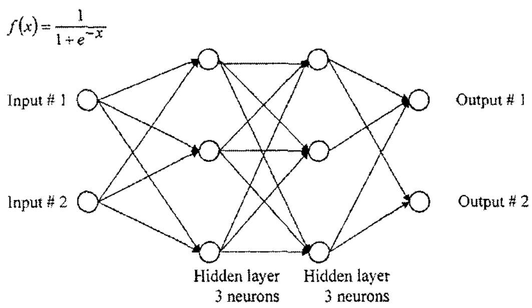

Fig. 4 General schematic diagram of a simple generic neural network

accurately, the impact of the subsurface heterogeneous hydraulic conductivity on the two-dimensional unsteady well draw down and its statistical variability based on minimizing the Root Mean Square Error (RMS-Error). Figure 4 shows a schematic diagram for a generic neural network.

Due to the extreme difficulty and heterogeneity of the investigated problem in the presented study, one specific neural network is designed and developed for each sub-simulation case (Interpolation and Extrapolation) among the two simulation cases (unsteady and spatial) for the two main groups. Table 3. shows the final neural network models for each sub-simulation case and their associated number of neurons.

The input and output layers represent the key input and output variables described previously for each sub-simulation case. It is very important to mention here that all the developed models incorporated the sigmoid activation function presented in Figure 3 except the last model for the spatial-extrapolation case, the Hyperbolic activation function is used. The Sigmoid function typically has a narrow region about zero wherein the output will be roughly proportional to the input, but outside this region the Sigmoid function will limit to full inhibition or full excitation, Shin (1994). The Sigmoid function can be expressed mathematically as follows:

$$f(x)=\frac{1}{1+e^{-x}} \tag{7}$$

On the other hand, the Hyperbolic function is shaped exactly as the Sigmoid one with the same mathematical representation but it ranges from -1 to $+1$ rather than from 0 to 1. Thus it has the interesting property that there is inhibition near 0, but values at either extreme will be excited to full level, but in opposite sense. In addition, the Hyperbolic function can be considered as a switch with an intermediate range where is can be discriminating, Shin (1994).

The training parameters of the various network models developed in the current study for the different sub-simulation cases are presented in Table 4. These parameters can be described with their tasks as follows:

Learning Rate (LR) : determines the magnitude of the correction term applied to adjust each neuron's weights during training process.
Momentum (M) : determines the "life time" of a correction term as the training process takes place.
Training Tolerance (TRT) : defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process.
Testing Tolerance (TST) : it is similar to Training Tolerance, but it is applied to the neural network outputs and the target values only for the test data.
Input Noise (IN) : provides a slight random variation to each input value for every training epoch.

Table 3 The developed neural network models for all the simulated cases

Group No.	Simulation case	Sub-simulation case	No. of layers	No. of neurons in Input layer	No. of neurons in first hidden layer	No. of neurons in second hidden layer	No. of neurons in output layer
1 (Draw down)	Unsteady	Interpolation	3	2	2	-	1
	Unsteady	Extrapolation	4	2	2	2	1
	Spatial	Interpolation	4	2	2	2	1
	Spatial	Extrapolation	4	2	2	3	1
2 (Monte Carlo)	Unsteady	Interpolation	3	2	5	-	1
	Unsteady	Extrapolation	4	2	3	3	1
	Spatial	Interpolation	4	2	5	4	1
	Spatial	Extrapolation	4	2	3	2	1

Table 4 Parameters used in the developed neural network models for all the simulated cases

Group No.	Simulation case	Sub-simulation case	LR	M	TRT	TST	IN	FG	SM
1 (Draw down)	Unsteady	Interpolation	1	0.9	0.01	0.03	0	1	0.1
	Unsteady	Extrapolation	1	0.9	0.03	0.05	0	1	0.1
	Spatial	Interpolation	1	0.9	0.03	0.05	0	1	0.1
	Spatial	Extrapolation	1	0.9	0.008	0.01	0	1	0.1
2 (Monte Carlo)	Unsteady	Interpolation	1	0.9	0.008	0.009	0	1	0.1
	Unsteady	Extrapolation	1	0.9	0.008	0.009	0	1	0.1
	Spatial	Interpolation	1	0.9	0.006	0.008	0	1	0.1
	Spatial	Extrapolation	1	0.9	0.004	0.006	0	1	0.1

Function Gain (FG) : allows a change in the scaling or width of the selected function.
Scaling Margin (SM) : adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst Software, Shin (1994), in preparing data for the neural network or interpreting data from the neural network.

8. Results and Discussion

As mentioned earlier, the current study investigates the impact of subsurface heterogeneous hydraulic conductivity on the two-dimensional unsteady well draw down resulting from a pumping well in the middle of a confined aquifer. To successfully simulate the stochastic heterogeneous behavior of the draw down using ANN, the analysis is divided into tow major groups. The first group simulates the unsteady and spatial behavior of the draw down as a function of the subsurface heterogeneity. While the second group simulates the Monte Carlo results for the unsteady and spatial behavior of the draw down variability.

8.1 First Group: Unsteady and spatial behavior of the draw down

This group of analyses investigates the impact of the subsurface heterogeneous hydraulic conductivity on the unsteady and spatial behavior of the draw down in the confined aquifer. This group is divided into two simulation cases ; unsteady and spatial ones.

8.1.1 Unsteady simulation case

To make the current presented study complete and to show the various capabilities of the ANN technique, two sub-simulation cases are considered and two ANN models are developed for the unsteady case. The first model coincides with the first sub-simulation case that can be named as the interpolation case. In this case, a wide domain of subsurface heterogeneous hydraulic conductivity and its associated draw down results is fed to the ANN model for training the network. Specifically, the ANN model network is trained with σ_f (standard deviation of the hydraulic conductivity) ranges from 0.1 to 1.0 hiding the values for σ_f=0.5 for prediction and testing the accuracy of developed model. The results of this interpolation case are presented in Figure 5. This figure shows the target required, ANN prediction, and the percentage relative error values between the target and the ANN prediction for the draw down at the well as a function of the pumping time. It is clearly shown from this figure how accurate the developed ANN model for predicting the draw down values at the well for the case of σ_f=0.5 when the network was trained with a large σ_f domain since the maximum percentage relative error between the target required draw down values and the ANN prediction ones was less than 1.0%.

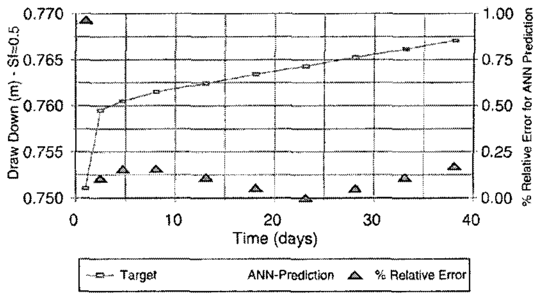

Fig. 5 Draw down prediction at the well using ANN and its % relative error compared with the target values for σ_f = 0.5, (Sf represents σ_f)

The second sub-simulation case and the second ANN model are designed for the extrapolation case. In this case a limited domain range of σ_f (from 0.1 to 0.7) and its associated draw down values at the well as a function of the pumping time is fed to the developed network for training. While the prediction accuracy of the developed ANN is tested for the draw down values for σ_f=1.0. Figure 6 shows the target required, ANN prediction, and the percentage relative error values between the target and the ANN prediction for the draw down at the well as a function of the pumping time for the heterogeneous case of σ_f= 1.0. It is clearly shown from this figure how accurate the developed ANN model for predicting the draw down values at the well for the case of σ_f=1.0 when the network was trained with a limited σ_f domain since the maximum percentage

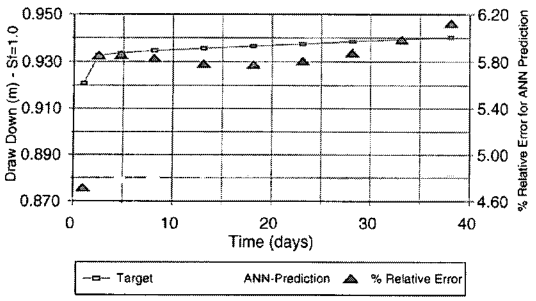

Fig. 6 Draw down prediction at the well using ANN and its % relative error compared with the target values for $\sigma_f=1.0$, (Sf represents σ_f)

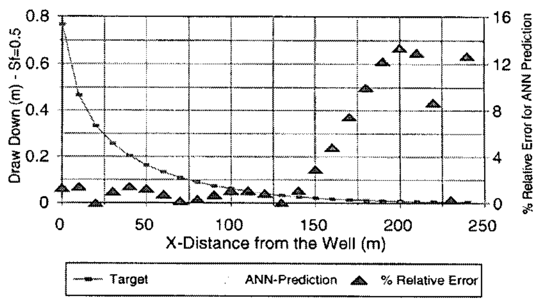

Fig. 7 Draw down prediction along the X-direction of the aquifer using ANN and its % relative error compared with the target values for $\sigma_f=0.5$ after 38 days of continuous pumping, (Sf represents σ_f)

relative error between the target required draw down values and the ANN prediction ones was less than 6.2%.

8.1.2 Spatial simulation case

This simulation case utilizes ANN technique to investigate the impact of the subsurface heterogeneous hydraulic conductivity on the spatial behavior of the draw down along the X-direction in the confined aquifer after 38 days of continuous pumping. In the current paper, only X-direction results are presented to show the applicability of using ANN in investigating the spatial stochastic draw down behavior, however, any spatial direction within the confined aquifer will have the same results obtained in this manuscript. The same two sub-simulation cases (interpolation and extrapolation cases) considered in the unsteady simulation case described previously are also considered in the spatial case. Two ANN network models are developed for the two spatial sub-simulation cases and their layering structures can be shown in Table 3. The results of applying the ANN model developed for the interpolation case spatially are presented in Figure 7. This figure shows the target required, ANN prediction, and the percentage relative error values between the target and the ANN prediction for the draw down along the X-distance from the well after 38 days of continuous pumping time. It is clearly shown from this figure how accurate the developed ANN model for predicting the draw down values for the case of $\sigma_f=0.5$ when the network was trained with a large σ_f domain since the

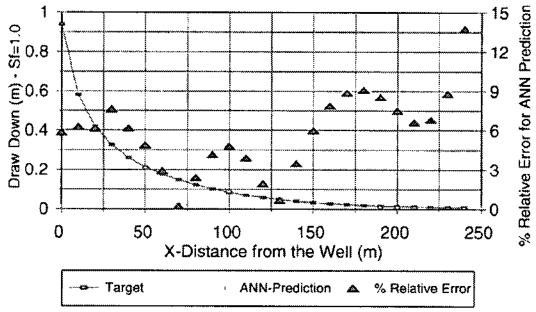

Fig. 8 Draw down prediction along the X-direction of the aquifer using ANN and its % relative error compared with the target values for $\sigma_f=1.0$ after 38 days of continuous pumping, (Sf represents σ_f)

maximum percentage relative error between the target required draw down values and the ANN prediction ones was less than 14.0% occurred only at the very small draw down values near the aquifer border.

On the other hand, the results of the developed ANN model for the extrapolation case are presented in Figure 8. Once again, this extrapolation case considers a limited range for σ_f (from 0.1 to 0.7) and its associated spatial draw down values for training the developed model. However, the spatial draw down for $\sigma_f=1.0$ is used for testing the prediction power of the developed ANN network model. It is presented in Figure 8. that the maximum percentage relative error between the target required draw down values and the ANN prediction results is less than 15% and it occurred at the far end of the aquifer where the draw down values are very small. While all the percentage relative error values from the well up to 230.0 m were less than 10%. These good results show the high accuracy of the developed model for this extrapolation case.

8.2 Second group : unsteady and spatial monte carlo

This group of analyses investigates the impact of the subsurface heterogeneous hydraulic conductivity on the unsteady and spatial behavior of the draw down variability represented by the standard deviation of the draw down in the confined aquifer. Basically this group simulates the Monte Carlo results produced by Abdin and Abdeen (1999). This group is divided into two simulation cases ; unsteady and spatial ones.

8.2.1 Unsteady simulation case

This simulation case is concerned with the unsteady behavior of the draw down variability at the well in the middle of the confined aquifer. Similar to what was investigated in the first group, two sub-simulation cases are also considered here namely ; interpolation and extrapolation as described previously. However, in the Monte Carlo group of simulations, the σ_f domain ranges from 0.1 to 0.5. The interpolation case trains the developed ANN model with the entire domain hiding the data for σ_f=0.3 and use them as a test for predicting the accuracy of the developed model. On the other hand, the extrapolation case trains the developed ANN network mode using a limited domain for σ_f from 0.1 to 0.3 and predicts the draw down standard deviation for the heterogeneous case of σ_f=0.5. The results of the interpolation and extrapolation cases are presented in Figures 9 and 10 ; respectively. These figures show the target-required values of the standard deviation for the draw down at the well as a function of the pumping time up to 38 days and the percentage relative error between the target and the predicted values. As it is clear from these figures that the maximum percentage relative error for the interpolation case was less than 2% and less than 5% for

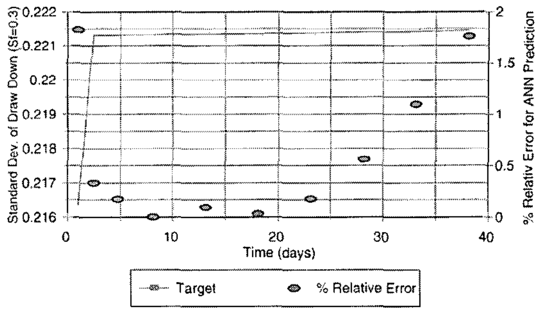

Fig. 9 Standard deviation of draw down prediction at the well using ANN and its % relative error compared with the target values for σ_f=0.3, (Sf represents σ_f)

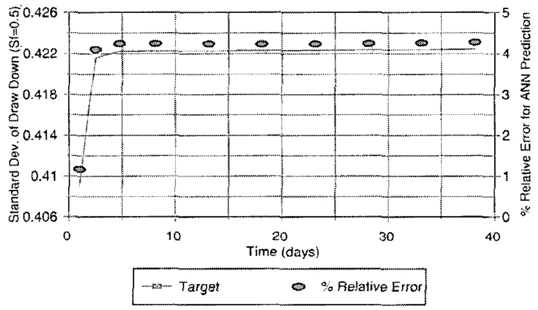

Fig. 10 Standard deviation of draw down prediction at the well using ANN and its % relative error compared with the target values for σ_f=0.5, (Sf represents σ_f)

the extrapolation case. These very small errors prove the capabilities of the ANN technique in simulating the Monte Carlo results for the unsteady standard deviation draw down at the well.

8.2.2 Spatial simulation case

This simulation case is concerned with the spatial behavior (along the X-direction) of the draw down variability within the confined aquifer away from the well. Similar to what was investigated in the first group, two sub-simulation cases are also considered here namely ; interpolation and extrapolation as described previously. Similar to the unsteady simulation case of the second group, the spatial simulation case considers the σ_f domain ranges from 0.1 to 0.5. The interpolation case trains the developed ANN model with the entire domain hiding the data for σ_f=0.3 and use them as a test for predicting the accuracy of the

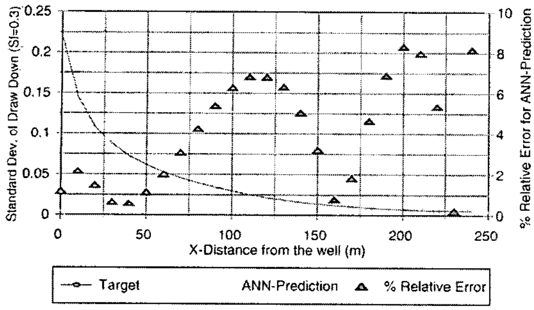

Fig. 11 Standard deviation of draw down prediction along the X-direction of the aquifer using ANN and its % relative error compared with the target values for $\sigma_f=0.3$ after 38 days of continuous pumping, (Sf represents σ_f)

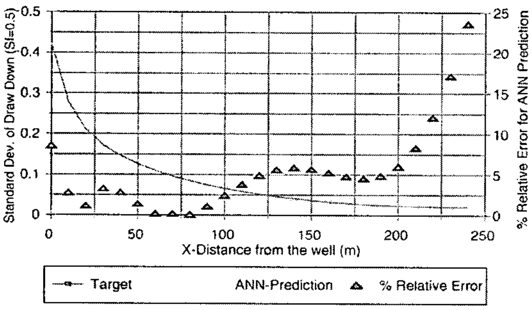

Fig. 12 Standard deviation of draw down prediction along the X-direction of the aquifer using ANN and its % relative error compared with the target values for $\sigma_f=0.5$ after 38 days of continuous pumping, (Sf represents σ_f)

developed model. On the other hand, the extrapolation case trains the developed ANN network mode using a limited domain range for σ_f from 0.1 to 0.3 and predicts the draw down standard deviation for the heterogeneous case of $\sigma_f=0.5$. The results of the interpolation and extrapolation cases are presented in Figures 11 and 12 ; respectively. These figures show the target-required values and the ANN prediction of the standard deviation for the draw down along the X-distance away from the well after 38 days of continuous pumping as well as the percentage relative error between the target and the predicted values. It can be noticed from Figure 11 that the maximum percentage relative error for the interpolation case was less than 10%. However, most of the percentage relative error for the extrapolation case presented in Figure 12 was also less than 10% except the last three values behind 220.0 m away from the well where the draw down variability was very small in these values. These small errors in the two figures prove the capabilities of the ANN technique in simulating the Monte Carlo results for the spatial standard deviation of draw down along the confined aquifer.

9. Summary and Conclusion

The current study was aimed towards investigating the applicability of using the artificial neural network (ANN) technique in simulating and predicting, with little computational effort, the impact of subsurface heterogeneous hydraulic conductivity on the unsteady two-dimensional stochastic behavior of a confined aquifer draw down resulting from a pumping well in the middle of the aquifer. The data used in the current study was the same data reported by Abdin and Abdeen (1999).

Two groups of simulations were considered in the current study ; The first group simulates the impact of the subsurface heterogeneous hydraulic conductivity on the unsteady two-dimensional well draw down using ANN. While the second group simulates the impact of the same subsurface heterogeneous parameter on the stochastic variability of the two-dimensional unsteady well draw down represented by its standard deviation. Specifically this second group utilizes ANN technique to predict the Monte Carlo results. Thereafter each group of simulation is divided into two simulation cases ; unsteady and spatial cases. The unsteady case utilizes the ANN technique to simulate and predicte the unsteady stochastic behavior of the draw down (first group) or its standard deviation (second group) at the well. On the other hand, the spatial simulation case incorporates the ANN technqiue to simulate and predict the spatial stochastic behavior of the draw down (first group) or its standard deviation (second group) along the confined aquifer after 38 days of contineous pumping. Several ANN netwrok models are developed for these simulation cases to successfully simulate the unsteady two-dimensional stochastic behavior of the draw down. The developed ANN models were first trained using part of the available data and their accuracy was tested against the remaining parts. The results of implementing the ANN technique in this study showed that this approach was capable of identifying relationship between different uncertain parameters with multiple input/output criterions. The ANN presented in this study was very successful in simulating and predicting the impact of various scenarios of subsurface heterogeneous hydraulic conductivity on the unsteady two-dimensional draw down in the investigated confined aquifer with very high accuracy and little computational efforts compared with the standard stochastic and Monte Carlo approaches.

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