Artificial Neural Network Technique For Predicting of Groundwater Level In Sarir Wellfield – GMMRP, SE Libya.

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Abstract
In this study, an application of Artificial Neural Networks technique (ANN) was presented to predict the confined aquifer water level (SWL) located in Sarir Wellfield, SE-Libya. Subsequent to instating initializing the model with (SWL) observed, the developed artificial neural networks back propagation model (BP-ANN) should be able to reproduce (SWL)using input variables, including aquifer transmissivity (T m^2/min),and wells location coordinate (E m,N m, Z m). The performance of ANN models was evaluated using the mean absolute percentage error (MAPE%) and the efficiency factor (E). The results indicated that, ANN technique was well suited for predicting the confined aquifer water levels at Sarirwellfield. According to the results observation, the (ANN3) model optimized with the Levenberg-Marquardt(LM) algorithms showed the most beneficial results with the minimum (MAPE%) value of (0.055) and maximum (E) value of (0.98), obtained for simulation of groundwater levels. The present research conclusively showed the capability of ANN to provide excellent estimation accuracy.

Key words: Confined Aquifer, BP-ANN, Groundwater level, Sarir Wellfield.

1. Introduction

Groundwater is one of the most important domestic, industrial and agricultural water resources of some country, for example, Libya, which gets low precipitation because of its area in a semi-arid region. Thus, the Libyan government built-up Great Man-Made River project (GMMRP) for transporting 6.5 Mm^3/day from aquifers located beneath the deserts to the coastal cities[1]. Subsequently, right now be focused on the Sarir wellfield situated at the Sirt and Al Kufra Basin (GMMRP-Phase I), on the grounds that the Sarir wellfield is the one of water supply resource of domestic and rural needs in Libya. Accordingly, it is important to legitimize the ground water right now legitimate arranging, which relies upon models to help the decision maker to take the correct steps in the planning and investment optimization of this project.

Other than one of the issues confronting hydro geological studies is the estimation of the data values such that confined aquifer water level in a given region, either because the data are missing or the site does not have measurements.

Ground water hydrology examines problems like prediction and distribution of confined aquifer water level. Involved processes are nonlinear, complex, multivariate with variables having spatial and temporal variability. These are expressed by complex partial differential equations, which are normally solved with considerable approximations using complex numerical models. Artificial Neural Networks (ANN) technique can be used in groundwater hydrology since it doesn't require governing equations and their related assumptions. Moreover, the reason for wider acceptability of artificial neural networks (ANN) technique can be attributed to its capability to develop computing tools, which may partially capture amazingly faster and complicated information processing ability of the brain.

Many studies have been conducted in the area of predicting groundwater level, such as :

Affandia, et. al,2007, in their research they examined and compared the capability of an artificial neural network (ANN) with five different back propagation (BP) algorithms, namely Gradient descent with momentum (GDM), Gradient descent with adaptive learning rate and momentum (GDX), The Fletcher-Reeves Conjugate gradient (CGF), Quasi-Newton (BGF), Levenberg-Marquardt (LM), and a radial basis function (RBF) architecture for estimating groundwater level fluctuation (GLF). Five daily measurements of GLF in an observation well provided the data for analyzing their models. An input model using six time lags to estimate actual GLF and 10 hidden nodes gave an optimum result. Based on their study results, they concluded an ANN models can be used for forecasting GLF for the purposes of groundwater management[2].

Sreekanth, et. al, 2009, examined the forecasting of groundwater level at Maheshwaram watershed, Hyderabad, India using the standard feed-forward neural network model trained with Levenberg–Marquardt algorithm. In their study models efficiency and accuracy were measured based on the root mean square error (RMSE) and regression coefficient(R^2). The ANN models provided the best fit and the predicted trend followed the observed data closely(RMSE = 4.50 and R^2 = 0.93). Thus, they concluded that ANN technique appears to be a promising tool for precise and accurate groundwater level forecasting[3].

Nair, and Sindhu, 2016, in their study, models for prediction of water table depth were developed based on Artificial Neural Networks(ANN) with different combinations of hydrological parameters. while the best combination input was confirmed with factor analysis method. The input parameters for groundwater level forecasting in their study were derived using Time Series Analysis (TSA). Mamom river basin in Trivandrum-Kerala, was chosen as the study area by them as its groundwater resources have been used as the main source for drinking and agricultural purposes. They concluded that, the ANN model gives the best performance when rainfall, humidity and potential evapotranspiration are given as input parameters during monsoon season. Moreover During non-monsoon season, best performance was obtained when temperature is added to the input parameters, which indicates the influence of temperature on the groundwater level during non-monsoon period. In addition They concluded since the trend of variation of groundwater level is same for predicted and observed cases, ANN models can be used for predicting groundwater level of Mamom river basin[4]. Khaki, et. al ,2016, their study main objective of using an artificial neural network (ANN) was to investigate the feasibility of feed-forward, Elman and Cascade forward neural networks with different algorithms to estimate groundwater levels in the Langat Basin-Malaysia. In order to examine the accuracy of monthly water level forecasts, effectiveness of the steepness coefficient in the sigmoid function of a developed ANN model was evaluated in their research. The performance of the models was evaluated using the mean squared error (MSE) and the correlation coefficient (R). Their study results indicated that the ANN technique was well suited for forecasting groundwater levels. Based on the observation, the feed-forward neural network model optimized with the Levenberg-Marquardt algorithms showed the most beneficial results with the minimum MSE value of (0.048) and maximum R value of (0.839), obtained for simulation of groundwater levels[5].

Al-Aboodi, et. al, 2016, the aim of their study is to predict groundwater level Safwan-Zubair area South of Iraq using ANN model. The data required for building the ANN model is generated using MODFLOW model (V.5.3). Three layers feed-forward network with Log-sigmoid transfer function were used in their study. The networks were trained using Levenberg-Marquradtback-propagation algorithm. The ANN modes were divided into two groups, each of four models. The input data of the first group include hydraulic heads, while, the input data of the second group include hydraulic heads and recharge rates. Based on results of their study it was found that; the best ANN model for predicting groundwater levels in the study area is obtained when the input data includes hydraulic heads and recharge rates of two successive months preceding the target month, the best structure of ANN model is of three layers feed-forward network type composes of two hidden layers, each of ten nodes, and the including of recharge rates as input data, beside the hydraulic heads has improved slightly the results[6].

This study illustrates the development and application of Artificial Neural Networks (ANN) to predict groundwater level in Sarir well field located in confined aquifer(SWL m). ANN models were used in this study are based on measured data from 126 wells distributed over the wellfield. ANN models were carried out to predict groundwater level by inputs consider of the aquifer transmissivity (Tm^2/min), and the wells location coordinates (Em,Nm,Zm). Three different type of ANNs structure were used to predict the groundwater level and compared to the observed one. The performance of different models structure of the ANN is used to identify the fluctuation of the groundwater level and provide acceptable predictions. The efficiency factor (E), Mean absolute percentage Error (MAPE%), and 95% confidence limit (95CI%) were chosen as the determination criteria of the best model.

2. METHODOLOGY AND AREA OF STUDY

2.1 Study Area

The Sarir wellfield is located in the southern part of the Sirtbasin. In the Sirtbasin, the aquifer consists of a thick deposit of Eocene clay and limestone with continental deposits of sand inter bed with some clay and limestone at the north of the basin as a result of the late of Cretaceous subsidence see Fig.1. The Sarir wellfield consists of 126 production wells with a capacity of 100l/s in order to reach the designed capacity of wellfield of 1Mm3/day. The wells are arranged into three parallel lines, with 1.3km distance between each well and with 10km distance between each line and 28 piezometer wells between and surrounding these production wells as showing in Fig.2. The depth to the main aquifer is around 220m and the aquifer thickness is around 250m. However, the .[depths of the wells are set at 450m [1].

2.2 Data Analysis:

Two different data sets of 126 wells were used in this study. The first group considers pumping tests data for the well itself (Tm2/min, SWLm),and the second is the well location (Em, Nm, Zm), both sets were obtained from the Great Man Mead River Authority (GMMRA). Additionally to distinguish the hydro geological characteristics of the 126 wells on Sarir well field, a pumping test had been led without observation wells with a steady pumping rate 120L/sec of period 1440 minuet. The all field estimation information, of the study area, presents to at Table 1. Figures 3 to 6 present the scatter graphs and contour maps for Sarir well field aquifer transmissivity (T m2/min) and static water level (SWL).

The most notable estimation of Sarir wellfield aquifer transmissivity is found at The Southeast, and upper East of the well field aquifer part and decline as one moves away toward the Northwest and West. The Sarir wellfield aquifer transmissivity regards show that the aquifer of good execution in agreement to transmissivity scales. Furthermore the static water level (SWL) at the wellfield is increase as one moves away toward the South of Sarir wellfield aquifer part.

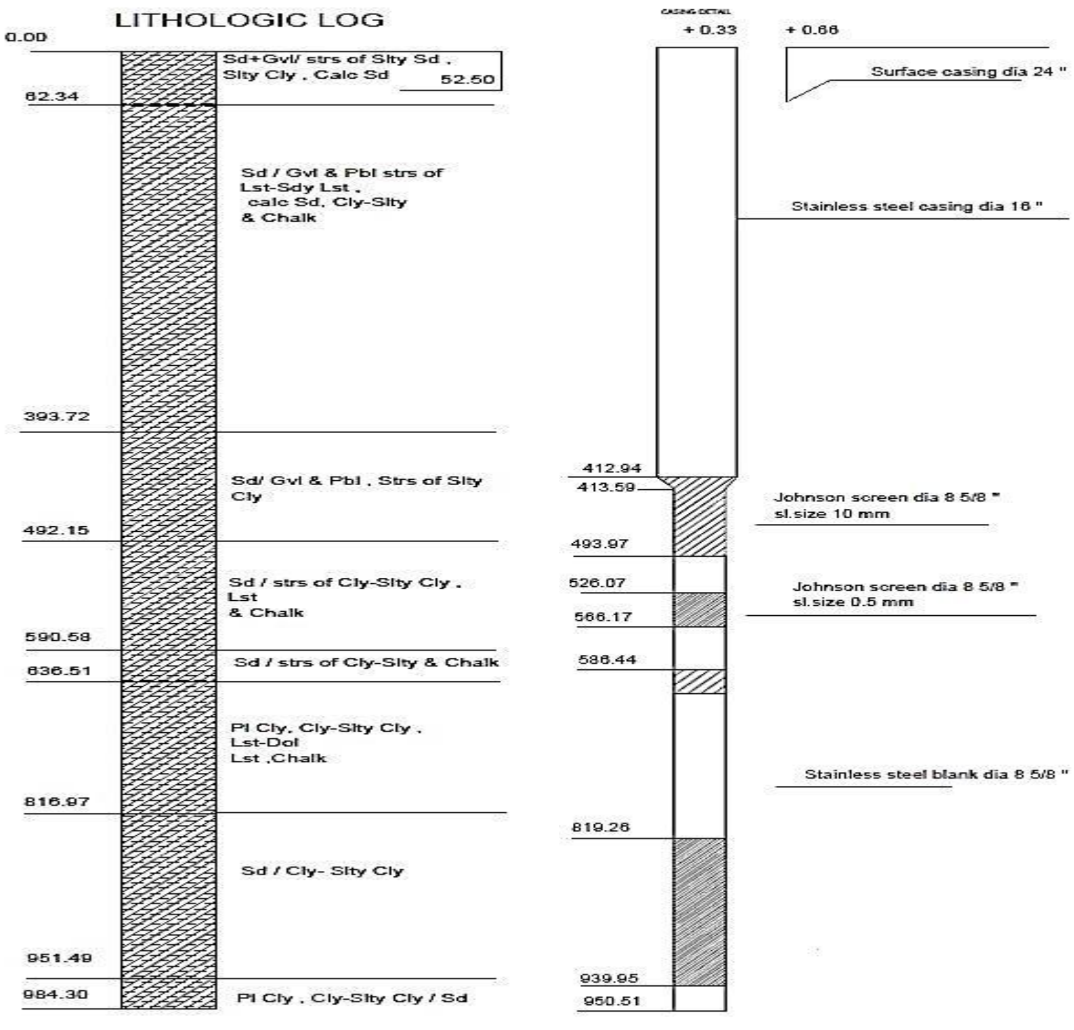

Fig. 1 The stratigraphic column of Sarirwellfield aquifer, and pumping well structure design (GMMRP,1991).

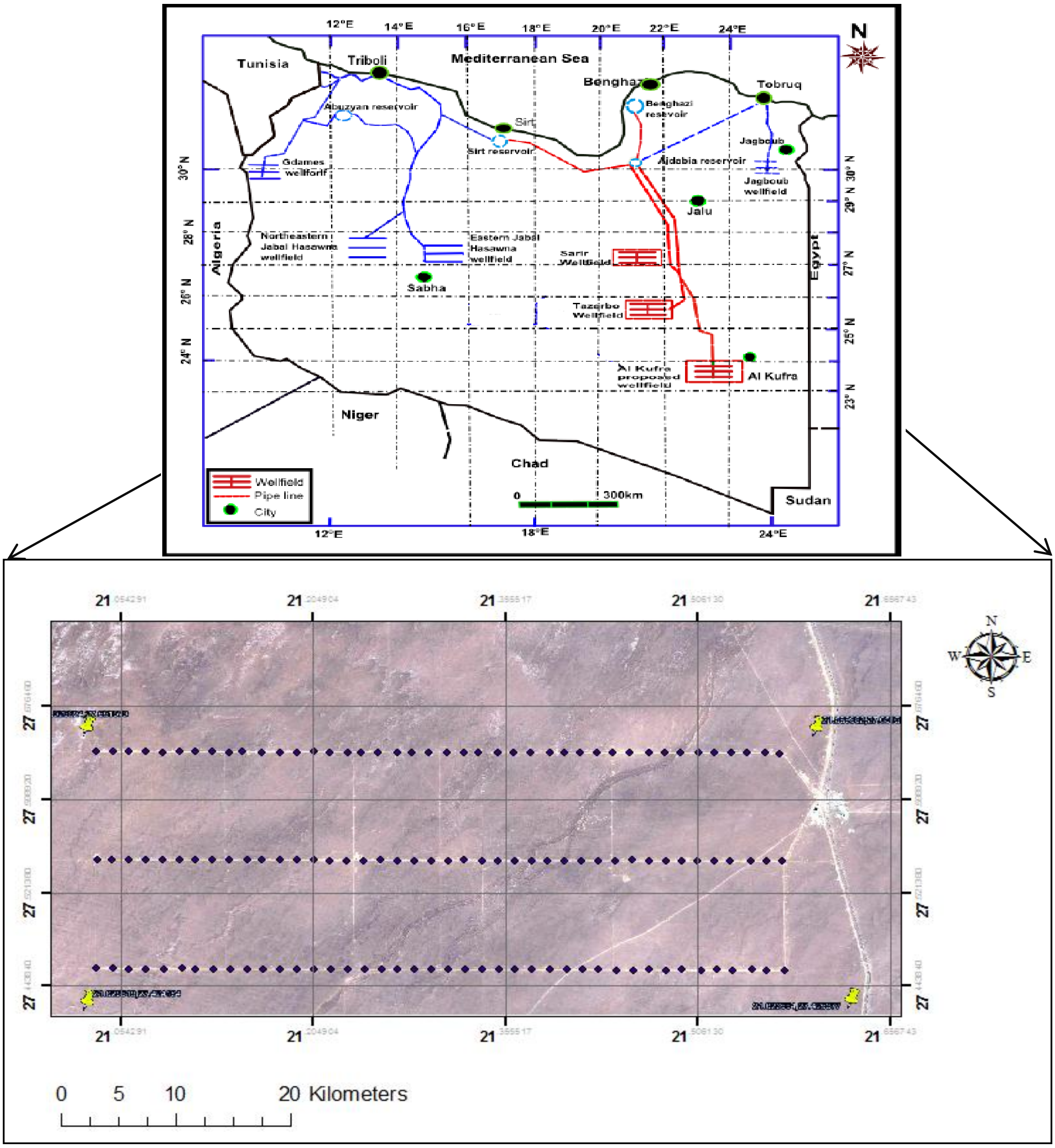

Fig. 2 Map of study area and location of Sarir wellfield.

Table: 1 Statically analysis of field information at Sarir wellfield-GMMRP.

	E m	N m	Z m	Transmissivity T m^2/min	Static waterlevel SWLm
Mean	529818.347	3047135.81	160.326	1.741	90.850
Max.	556746.563	3057223.25	179.980	4.975	93.320
Min.	503489.687	3036983.50	143.040	0.165	88.660

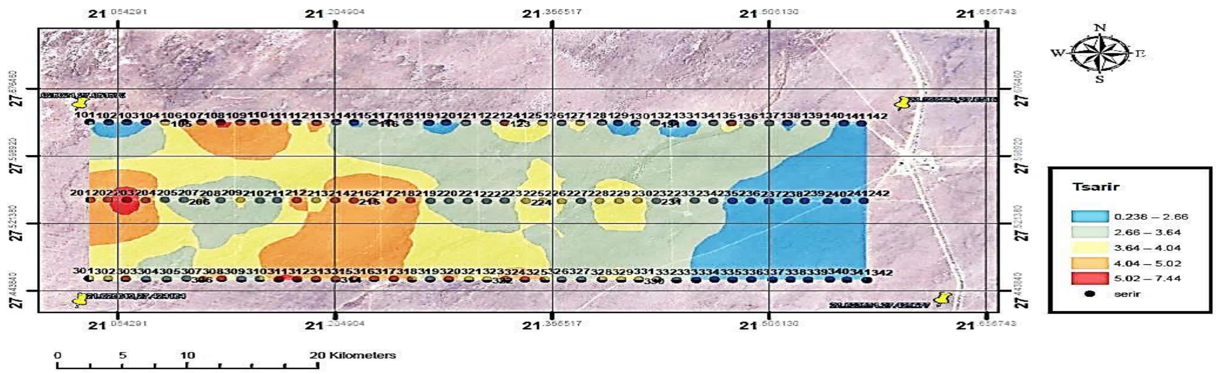

Fig.3 Contour map for Transmissivity T m^2/min of Sarir wellfield aquifer**.**

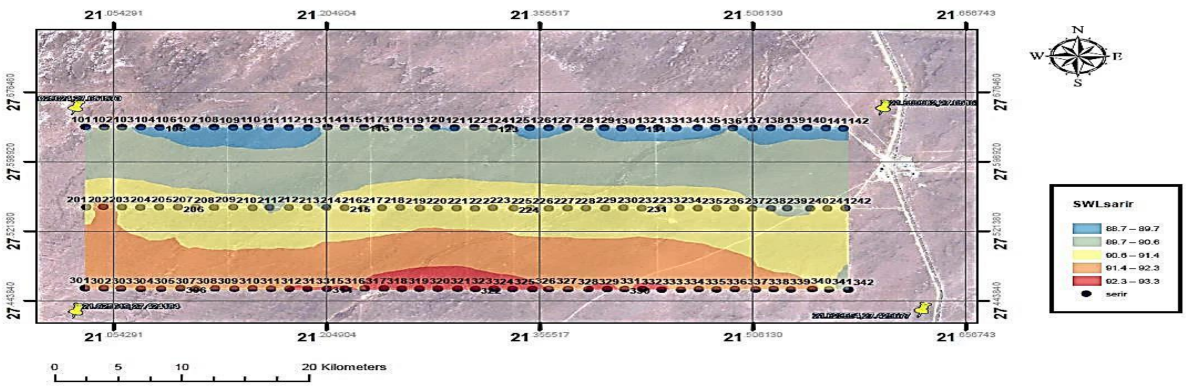

Fig.4 Contour map for confined aquifer static water level SWL m at Sarir wellfield**.**

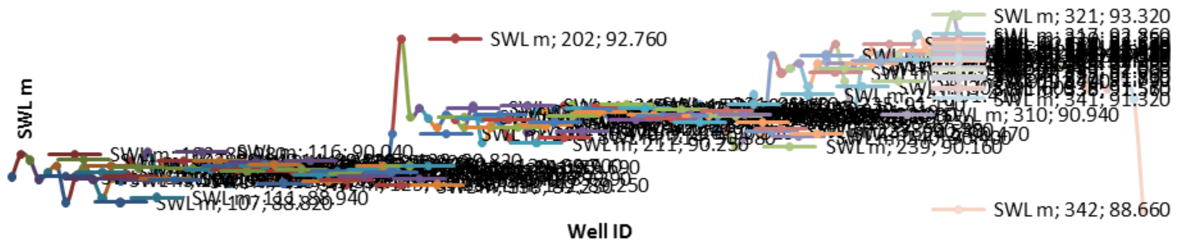

Fig.5 Static water level (SWLm) values at Sarir wellfield**.**

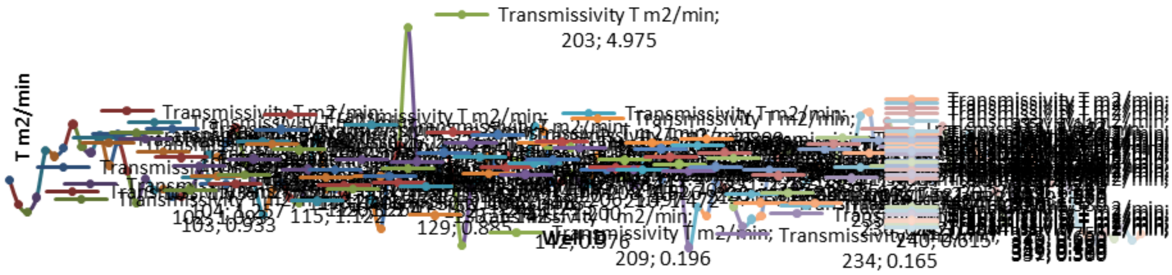

Fig.6 Aquifer transmissivity (T m^2/min) values at Sarir wellfield**.**

2.3 Artificial Neural Networks (Ann) Technique

Artificial Neural Networks (ANN), are a form of computing inspired by the functioning of the brain and nervous system. Neural networks consist of a set of neurons or nodes arranged in layers, and in the case weighted inputs are used, these nodes provide suitable inputs by conversion functions. Each neuron in a layer is connected to all the neurons of the next layer but without any interconnection among the neurons in the same layer. The weight learned for each neuron in ANNs model remains internal, and therefore, their associations with physical systems are often overlooked**.** The feed forward ANN has been adopted in many hydrological modeling studies because of its applicability to a variety of different problems. Noted that more than one hidden layer may require in feed forward networks because a three-layer network can generate arbitrarily complex decision regions. Also, the appropriate input vector to the ANN model can be identified according to the procedure of the modeler. Back propagation is the most popular algorithm used for the training of the feed forward ANN. An objective function that considers both the ANN's structure and error, minimizes a linear combination of the resulting ANN's squared errors, weights, and biases in order to develop a less complex model at the end of training the resulting network has good generalization qualities. The Levenberg–Marquardt (LM) training algorithm is a trust region based method with a hyper-spherical trust region[7]. This algorithm was implemented in this study using the Neural Network Toolbox of MATLAB, an example of developed structure of ANN model with **4** inputs see Fig.**7**.

2.4 Models Performance Verification :

In this study, a several statistical parameters were used to evaluate the performance of prediction ANN models, which were given by the following relations:

1- Mean absolute percentage error (MAPE%):

$$MAPE\% = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{SWLobs._i - SWLpre._i}{SWLobs._i}\right| \quad (1)$$

2- Efficiency factor (E):

Efficiency factor (E = 0 to 1) is calculated on the relationship between the predicted and observed mean deviations and it can show the correlation between the predicted and observed data:

$$E = 1 - \frac{\sum_{i=1}^{n}(SWLobs._i - SWLpre._i)^2}{\sum_{i=1}^{n}(SWLobs._i - \overline{SWLobs._i})^2} \quad (2)$$

3- 95% confidence limit (95CI%):

The Standard error of the mean observed data is given as : $s_x = \frac{s}{\sqrt{n-1}}$

The quantity $\frac{\overline{SWLobs.} - SWLobs.}{Sx}$ has a t-distribution with (n-1) degrees of freedom, and for 95% confidence limit:

$$\overline{SWLobs.} - 1.95\left(\frac{s}{\sqrt{n-1}}\right) < \overline{SWLpre.} < \overline{SWLobs.} + 1.95\left(\frac{s}{\sqrt{n-1}}\right) \quad (3)$$

The value on the left side of the inequality yields the lower limit, and on the right side yields the upper limit for the mean observed data , known as the Confidence Level.

Where:

n= Number of data.

SWL.obs.= Observed value.

SWL.pre.= Predicted value.

S = Standard deviation.

$\overline{SWLobs.}$ = The average of the observed data.

A superior fit model, with zero demonstrating MAPE% and high estimation of E. Consequently the model if have a good performance will produce a results within the range of 95CI% of the mean observed data. In a specific order, the prediction models are utilized to create information which save the primary factual attributes of the observed information[8].

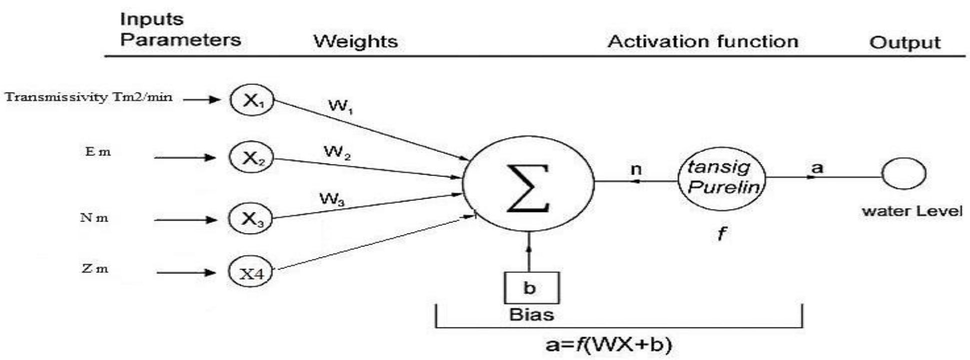

Fig.7 Developed Structure of ANN with 4 inputs

3.predicting of Groundwater Level in Sarir Wellfield using Artificial Neural Network Technique :

Construction ANN model utilization Neural Networks (BP-ANN) which built in MATLAB program version 15. Different ANN structure had been investigated to find optimum ANN model. The optimum neuron number in each hidden layer was also investigated.In order to develop ANN models for prediction sarir wellfield static water level, the data is divided into two groups randomly: training data, accounting for 90 percent and testing and validation data, making up 10 percent of the total data.

The ANN models were trained using Levenberg–Marquardt (LM) algorithms with activation functions for the hidden and output layers 'logsig' and 'purelin' functions, respectively. In ANN models the number of neurons in the hidden layer were found by a trial and error procedure. ANN model structure as following :

ANN1:(1,400,1) indicates having1, 400and 1 for the input which is, (T m^2/min), hidden layer and output(SWL m), respectively.

ANN2:(2,400,1) indicates having 2, 400 and 1 for the inputs are(Em, Nm, Zm), hidden layer and output (SWL m), respectively .

ANN3:(4,400,1) indicates having 4, 400 and 1 for the inputsare (T m^2/min, Em, Nm, Zm), hidden layer and output (SWL m).

Furthermore the data divided in to :114 values for model training, 6 values for model validation, and6 values for model testing) see Fig 8.

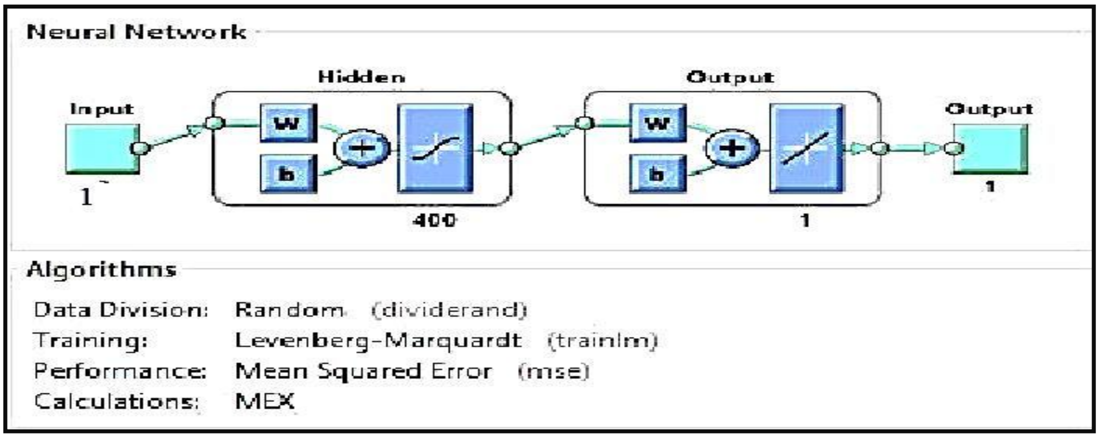

Fig. 8 ANN1,ANN2,ANN3 models structure used in this study.

4.Results and Discussion

As has been explained, the utilized dataset including (Tm^2/min, and wells location Em, Nm, Zm) from Sarir wellfield confined aquifer which were defined as the external inputs for determining the groundwater levelSWL m.

Based on the results of ANN models showing at Table2,three different models were implemented by three inputs combination, also improved by the accuracy with respect to MAPE%, E, and CI 95%. Over all ANN models showing best prediction for all input combination in both tests and validation data group. Figure 9presents the comparison between the predicted and observed SWL m data romANN1,ANN2,and ANN3. Looking into the models result, it is found out that, prediction of the SWL m in the first model has a greater magnitude of error, as it has fewer input parameters. Therefore, this indicated the inefficiency of the simulating and training algorithms. In the second and third models the error declines as the simulating and training algorithms were kept constant. It was revealed that error dwindles to its minimum as the number of input neurons decreased and an extra layer was built into the third model .The best architecture was obtained from (ANN3-(4,400,1)) had been selected based on minimum value of MAPE%=0.055% and maximum value of E=0.98.

Figurer 10 the distribution of the observed and predicted data (the vertical axis) and the well ID (the horizontal axis) in the testing and training stage of the ANN3 model. It should be noted that the closer the data get to a one –to-one diagram, the more reliably the model evaluates the SWL proportion. Also the results show a significant superiority of the combined model ANN3 to the well latitude, longitude. The advantage prediction, it makes possible to predict spatially SWLm distribution with access to other parameters such as T m^2/min.

Table:3 Error statistics for input combinations using ANN models in test and validation stage.

Inputcombinations	ANN model architecture	MAPE%	E	The average Predicted SWL m	**95% CIObservedSWL m**
T m^2/min	ANN1 (1,400,1)	0.206	0.820	90.884	
Em , Nm, Zm	ANN 2 (3,400,1)	0.094	0.975	90.840	90.645-91.056
T m^2/min,Em, Nm, Zm	ANN3 (4,400,1)	0.055	0.982	90.853	

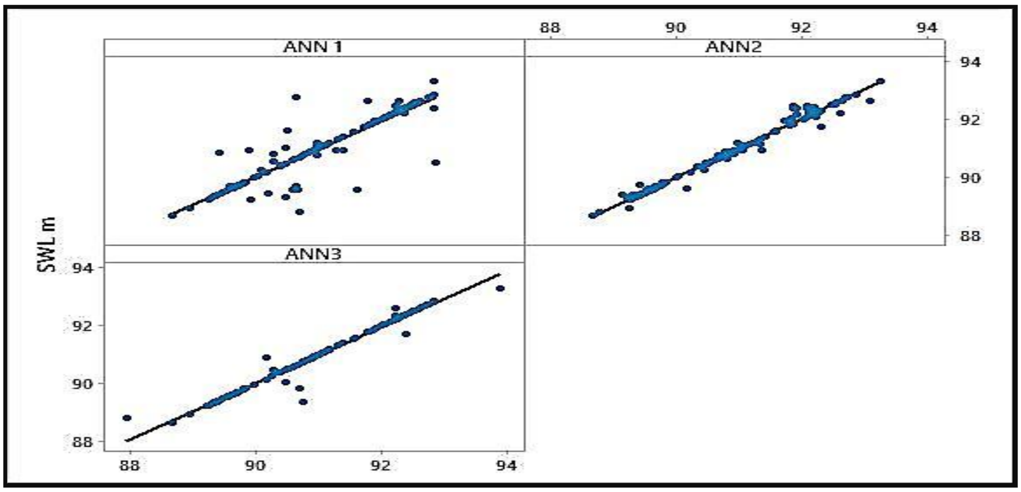

Fig.9. Comparison of the estimated and observed data (SWL m)at Sarir wellfield

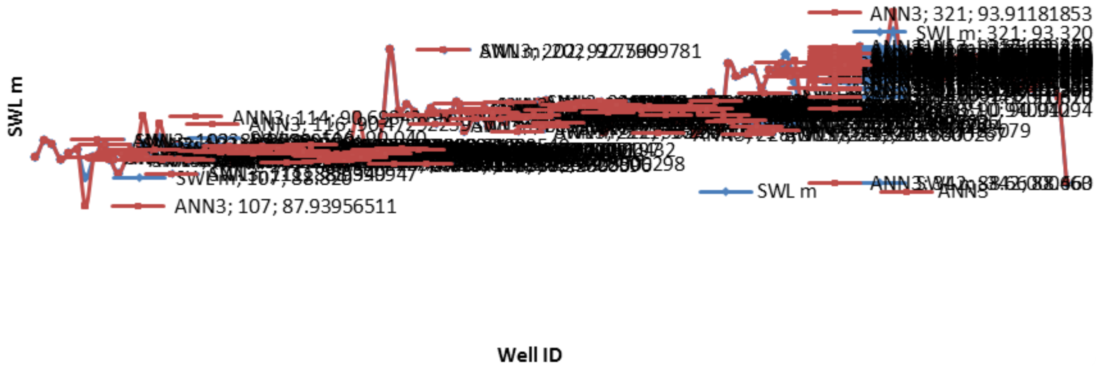

Fig.10. Comparison between the observed and predicted (SWL m) at Sarir wellfield from ANN3based on well ID.

5. CONCLUSION

In this study, prediction of the confined aquifer water level (SWL) in Sarir wellfield located at SE-Libya, was carryout via the ANN technique. The input variables to construct the ANN models were: the wells Cartesian coordinate(Em, Nm, Zm) and the aquifer transmissivity T m^2/min. The Levenberg–Marquardt (LM) algorithm was used to train the back propagation feed forward ANN models. The ANN models performances were compared using the coefficient of determination (E), mean absolute percentage error (MAPE%), and 95%CI confidence interval. ANN3 model performed superior to the other models in predicting (SWL) with high E=0.98 and lowest MAPE=0.055% and have predicted mean within the range of observed 95CI%.

It goes through the groundwater level location and the aquifer transmissivity, played a good pronounced role in predictions of the groundwater level (SWL) at Sarir wellfield. Moreover, ANN3 model, it makes possible spatially prediction of SWL m distribution with access to other parameters such as aquifer transmissivity. This is a quick and cost-effective method for management practices. Besides, the spatial variability of the groundwater level will assist the water resource managers and policymakers in the development of groundwater resources in the study area and Libya.

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