Groundwater Water Level Prediction in Wadi El Jezzy Catchment Using ANN

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Abstract—**Ground water is a major source of water in Oman for irrigation, water supply and industrial uses. The ground water level fluctuations depend on several factors such as rainfall, seepage, pumping etc. There are 127 00 wells in the Sultanate of Oman and the water level in these wells is monitored by the Ministry of Regional Municipality and Water Resources. These Information are important for the estimation of the ground water resources availability and the management of this vital source. In this study Artificial network models were developed to forecast monthly water levels for three wells in Wadi El Jezzy Catchment. These models were trained using the backpropagation algorithm. The study has shown that ANN can be used to forecast accurately monthly ground water level and also water levels for two months ahead.**

Index Terms—**Ground Water Level, Wadi El Jezzy, Artificial Neural Networks, Backpropagation.**

I. Introduction

Oman is in the world's arid belt and groundwater is the main source of water for meeting the water demand. It is the stockpile that is usually used when surface water is not available. It represents about (78%) of the water supply in the Sultanate. Groundwater has agricultural, domestic, and industrial uses and is acquired by constructing and operating extraction wells. The flow of the main groundwater in Oman begins from the Western Al Hajar Mountains and Dhofar Mountains. In each mountainous region the alluvial sedimentary in the wadi beds make excellent ground reservoirs that contain renewable water resources of good quality due to the recharge received from the rains, surface water flows, and water infiltration from the nearby ground reservoirs and solid gravel beds. As for the flows that go to the sea, it recharges the extended wide ground storages under the coastal plains.

Oman is a country with different weather systems which are dominating in particular seasons. Two distinct seasons are prevailing namely (November to April) and Summer(may to October) affected by various meteorological mechanisms throughout the country. The rainfall although scanty is the only source of natural water replenishment while groundwater is the essential natural source of water supply.

Rainfall is ranging from 50 mm in the interior to 300mm in the north Oman Mountains while the general average is about 100mm.

Wadi El Jizzi catchment has important reserves of groundwater which are heavily exploited for agricultural and industrial use. Sohar has seen a rapid industrial growth in the last decade and this is mainly due to the establishment of Sohar Port.

Monitoring and management of groundwater resources is achieved by monitoring the ground water levels in the well through measurement and using computer models to forecast the water levels in the wells. Recently, several researchers investigated the use of Artificial Neural Networks to model the water level fluctuation in well.

Shaoyuan et al [1] applied a three layer back propagation of artificial neural network to investigate the effects of hydrological, meteorological and human factors on the ground water levels for two regions in the Minquin oasis, located in the lower reach of Shiyang river Basin, in Northwest China, Jothiprakash and Suhasini [2] developed ANN model to predict ground water level in Sri ram Sagar reservoir project in Andhra Pradesh, Ahmad Abrishmachi et al [3] investigated the use of ANN to forecast monthly ground water level for Teharan-Karaj area, Uruya Weesakul et al [4] proposed a simple linear Genetic Algorithm (GA) model used to monitor and forecast fluctuation of groundwater table in Bangkok area and its vicinity. Zahra and Gholamreza [5] used the Artificial neural networks to forecast ground water depth in an observation well in UNION county, New Jersey, US, M. Kavitha and K.B. Naidu [6] compared ANN and ANFIS models for the prediction of groundwater level in Thurinjapuram watershed, Tamilnadu, India and to identify the most fitted model to the study area. Coulibaly et al[7] applied three different ANN models to calibrate relatively short length of groundwater level in the Gondo aquifer, Burkina faso.

II. Study Area

Wadi Al-Jizi catchment is located near Sohar which is the third largest town of the sultanate and the main commercial center in Al-Batinah. Total area of it is about 1154 km^2. It is

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located at an elevation of 12 meters above sea level at coordinates 24°23'12" N and 56°41'47" E in DMS (Degrees Minutes Seconds) or 24.3867 and 56.6964 (in decimal degrees).

Sohar is currently experiencing significant investment and economic shifts making it the focus of attention of many local and international investors and businessmen. This change is due to a series of investment projects and economic giant in Sohar industrial area where Port of Sohar is located. Established in 2002, the port has a strategic importance due to its nearness to the Strait of Hormuz.

Groundwater system in Jizzi region is heavily overexploited mainly for irrigation purposes and increasing industrial demand resulting in a severe deterioration of water quality and quantity accompanied in continuous saltwater intrusion wedge along the coast. It is therefore, important to monitor and forecast the ground water resources.

Several wells are exploited in Wadi Jezzy catchment (as shown in figure 2), the Ministry of Regional Municipality and Water Resources is monitoring the variation of the ground water level by collecting data from several wells. In this study it is proposed to develop an ANN model which will predict the monthly water level for the selected well. For this pupose. monthly data for three wells were used in these study. Data for Ground Water levels from 1999 to 2012 for JA-4 and JA-5 wells and from 1982 t0 2102 for LAV-SP were collected from Ministry of Regional Municipality and Water Resources

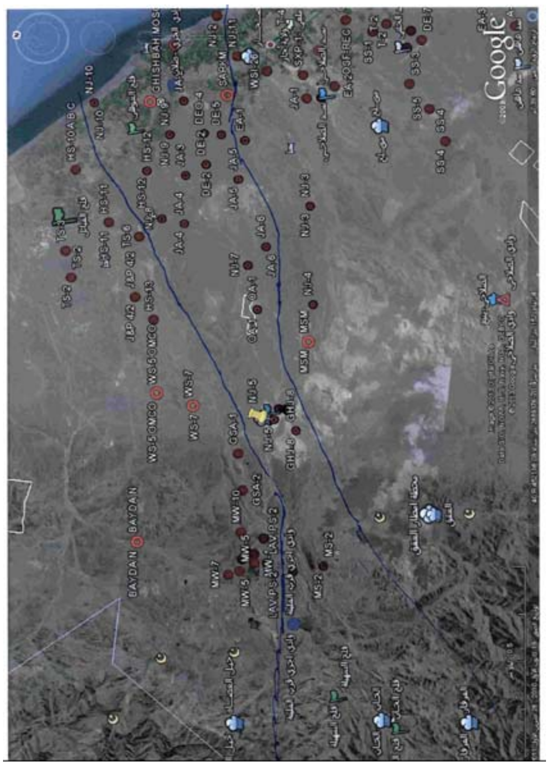

Figure 1: Weels in Wadi EL Jizzy Catchment

III. Artificial Neural Networks

ANN is potentially useful in situations where the underlying physical process relationships are not fully understood and well-suited in modeling dynamic systems on a real-time basis. The neural networks operate on the principle of learning from the training set. Before training the network does not have any prior knowledge about the problem.

In this study, feedforward network was considered for the analyses. The network was trained using the Backpropagation algorithm. BP network was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Properly trained BP networks tend to give reasonable answers when presented with inputs that they never seen. Typically a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without having to train the network on all possible input/output pairs.

IV. IV Model Development

In this study, monthly ground water levels were selected for training and testing of the networks. The ANN developed were trained with various number of neurons in the hidden layer. The input nodes contained antecedent ground water level whilethe output was water level for the month. In order to investigate the number of antecedent months required for satisfactory predictions, three different ANN models were developed, labeled as M1, M2, and M3.These models are given by the formulas:

$Model\ \ M1$

$$W(t) = f[W(t-1)] \qquad (1)$$

$Model\ \ M2$

$$W(t) = f[W(t-2), W(t-1)] \text{ ....}(2)$$

$Model\ \ \ M3$

$$W(t) = f[W(t-3), W(t-2), W(t-1)] \text{.....}(3)$$

Where, t = time, W = Ground water level, t: month

Simulations of ground water level with 2 months ahead were done with input nodes containing antecedent monthly ground water level. The generated output was water for the next 2 months. The number of output nodes equal to the required numbers of months ahead. The models developed for the next 2 months ground water level prediction are can be presented with the following equation:

Model 2MH

$$W(t, t+1) = f[W(t-3, t-2, t-1)] \text{.......}(4)$$

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V. TRAINING AND TESTING THE MODEL

Networks constructed were trained with different number of neurons in the hidden layer, learning rates, learning algorithms and length of simulation data. The networks were simulated using 10 to 200 neurons in the hidden layer and only one neuron in the output layer. Learning parameters selected varied from 0.1 to 0.5.

The network was trained using 3 different backpropagation algorithms, namely Resilient Backpropagation (*trainrp),)*, Scale Conjugate Gradient *(trainscg)* and Fletcher Reeves Conjugate Gradient*(traincgf)*. *Trainr p*is generally much faster than the standard steepest descent algorithm and it requires only a modest increase in memory requirements that suits network with sigmoidal transfer function. *Traincgf*on the other hand produces generally much faster convergences than steepest descent directions and requires only a little more storage than simpler algorithms. *Trainscg*was designed to avoid time consuming line search and has modest storage requirements.

The performances of the networks were measured by coefficient of correlation, *R*, Value of R is given by the following equation:

$$R = \frac{\sum_{i=1}^{i=n}[Q_m(t_i) - \overline{Q_m(t_i)}][Q_s(t_i) - \overline{Q_s(t_i)}])}{\sqrt{\sum_{i=1}^{i=n}[Q_m(t_i) - \overline{Q_m(t_i)}]^2 \sum [Q_s(t_i) - \overline{Q_s(t_i)}]^2}}$$

It should be noted that an R value of 1.0 implies a perfect fit.

VI. RESULTS AND DISCUSSION

A. Learning Algorithms

Learning algorithm selected were Resilient Backpropagation (trainrp), Scaled Conjugate Gradient (trainscg) and Fletcher-Reeves Conjugate Gradient (traincgf). In general, models trained using all three algorithm gave high R results. Based on Table I, the optimum result was obtained when using trainscg algorithm. It has the highest value compared to prediction with trainrp and traincgf.

Table I influence of learning algorithm used

Learning Algorithm	R (Testing)
Trainrp	0.9325
Traincgf	0.9462
Trainscg	0.9753

B. Learning Rate

The learning rates were varied from 0.1 to 0.5 to improve the results. Generally learning rates did not show any significant changes in the results, however the optimum R was obtained for a learning rate of 0.2 or 0.3.

Table II Influence of learning rates

Learning rate	**R (testing)**
0.1	**0.8989**
0.2	**0.9469**
0.3	**0.9341**
0.4	**0.9316**
0.5	**0.9479**

C. Number of Neurons in Hidden Layer

The number of neurons in the hidden layer was varied from 10 to 200. It can be seen from Table III that increasing the number of neurons increases the correlation however very high number of neurons is not good and the optimum is between 20 to 30.

Table III : Effect of Number of Neurons

Number of neurons	**Testing. R**
10	**0.9072**
20	**0.9335**
30	**0.9367**
50	**0.9351**
100	**0.9217**
200	**0.8948**

D. Length of training data

Monthly data for wells were used in this investigation, each with different combination of training and testing data. The length of training data for JA-4 and JA-5 were about 8 years and tested for about 5 years. But for the third well LAV-SP, the length of training was about 21 years and tested for 9 years. From table IV it can be seen that wells simulated with longer training data gives better results compared to those with limited training data. Longer training data gives the ANN model more examples to learn from. In this study, the optimum performance was given by LAV-SP well, which was trained with 21 years of data and with 9 years tested data.

Table III : Effect of length of training data

Well	**Testing. R**
JA-5 Well	0.1432
JA-4 Well	0.6417
LAV-SP well	0.9367

E. Number of Antecedent Data

Antecedent data used in this study were 1,2 and 3 months. From the analyses of the results networks using 3 months of antecedent data was found to give optimum results.

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Table V Best results of the third well for M1, M2 and M3

The models	Testing. R
M1	**0.9090**
M2	**0.9236**
M3	**0.9367**

F. Prediction of water level with 2 month ahead

ANN network tested in this investigation has shown its capability to predict accurately monthly water level. LAV-SP well. It was also found they give reasonable results in predicting water level with 2 month ahead with a coefficient of correlation equal to 0.91 as shown in Table VI.

Table VI Water level simulation for 2 month ahead

Learning rate	R (training)	R (testing)
0.1	0.90837	0.89627
0.2	0.90232	0.90398
0.3	0.90072	0.90783
0.4	0.90605	0.88763
0.5	0.91177	0.91014

VII. Conclusion

Artificial Neural Network (ANN) models have been successfully applied to forecasting the groundwater levels for Wadi El Jezzy catchment in Oman. The main parameters in calibrating the model to obtain good results are the length of the data and the number of antecedent data. It was also found that the ANN can model reasonably well ground water level with two months ahead.

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