Artificial Neural Network Technique for predicting groundwater in Bida Basin, Mokwa Niger State, Nigeria

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ABSTRACT

In this paper, groundwater level during the dry season in Bida Basin, Mokwa is predicted. An Artifitial Neural Network (ANN) was applied to investigate the practicability of mass balance equation for the network training and testing. The Feed Forward Levenberg Marquardt (FFLM), Recurrent Neural Network and cascade with Resilient Back propagation for different algorithms was used to calculate groundwater levels from October to April which is dry season in Mokwa, Bida Basin. The performance of the models was evaluated using Mean Square Error (MSE) and Correlation Coefficient. Two lithological group: unconfined and Semi – Confine were considered and Climatic data from January 2013 to December 2018 was used for the network training and Testing. The results show that the Feed Forward Levenberg Marquardt (FFLM) is the best overall performance for groundwater prediction in Mokwa with Mean Square Error (MSE) of 3.94 and corresponding correlation coefficient of 0.85, these means that the depth to groundwater levels in Mokwa increases from December and reached its highest level in April and reached its lowest level in September. It is observed that Actual Groundwater level in Mokwa is 27.19018 million cubic m for the total of 15 hectares and the Predicted Groundwater level is 26.7889 million cubic for the total of 15 hectares while the difference between Actual Groundwater level and Predicted Groundwater level is 0.40128. Artificial Neural Network ANN techniques were well suited for groundwater prediction level.

***Keywords**: aquifer, simulation, groundwater level*

1.0 INTRODUCTION

Harsh et al (2016), made it known that, Artificial Neural Network (ANN) is gaining prominence in various applications like pattern recognition, weather prediction handwriting recognition, face recognition autopilot and robotics. In their view Maier and Dandy (2000) suggested that there needed to be a shift in the focus of ANN research from the application of ANNs to various water resources case studies to issue addressing a number of methodological issues of ANN research from the application of ANNs.

Andrej et al, (2018), defined Artificial Neural Network (ANN) as a mathematical model that tries to simulate the structure and functionalities of biological neural networks.

Mao Xiaomin et al (2002) used Artificial Neural Network for groundwater prediction level in Dawu Aquifer of Zibo in eastern China, An auto Correlation analysis of the groundwater level which shows that the monthly groundwater level was time dependent was the first step they took as an analysis of their model. An auto Regression artificial neural network (ANN) model using back – propagation algorithm were then used to predict the groundwater level. Their results show that the model especially in testing period, which indicates that the model can describe the relationship between the groundwater fluctuation and main factors that currently influence the groundwater level Groundwater is essential and highly valuable for domestic, industrial and irrigation use in Arid and Semi- arid region. Groundwater modelling is not only important for environmental protection but also maintaining the groundwater equilibrium system, controlling groundwater level fluctuation and protecting against severe Land subsidence. These resources commonly are free from pathogenic factors, and have high quality, usually do not need chemical treatment (Moharram et al, 2013). It is widely recognized that many countries are entering an era of severe water shortage Seckler (1990). The prediction based on ANN techniques are then compared to actual measurement recorded during a subsequent monitoring period. The ANN models were developed based on Feed Forward Neural Network with Levenberg Marquardt (FFLM), Feed Forward Neural Network with Resilient Back Propagation (FFRP), Feed Forward Neural Network with Scaled Conjugate Gradient (FFSCG), Feed Forward Neural Network with BFCG quasi Network (FFBFG), Feed Forward Neural Network with Fletcher Reeves Conjugate Gradient (FFCGF), Recurrent Neural Network with Levenberg Marquardt (RNLM), Recurrent Neural Network with Resilient Back Propagation (RNRP), Recurrent Neural Network with Scaled Conjugate Gradient (RNSCG), Recurrent Neural Network with BFCG quasi Network (RNBFG), Recurrent Neural Network with Fletcher Reeves Conjugate Gradient (RNCGF), Cascade Forward Network with Levenberg Marquardt (CFLM), Cascade Forward Network with Resilient Back Propagation (CFRP), Cascade Forward Network with Scaled Conjugate Gradient (CFSCG), Cascade Forward Network with BFCG quasi Network (CFBFG), Cascade Forward Network with Fletcher Reeves Conjugate Gradient (CFCGF), In this paper we propose to show the difference between the Actual groundwater level and Predicted groundwater level

2.0 Model Formulation

2.1 Statistical Indices

Statistical indices correlation coefficient (R), Mean Square Error (MSE), Epoch, were used to evaluate the best fitting between observed and predicted data.

2.2 Artificial Neural Network

An artificial neural network (ANN) is a computational mode based on the structure and function of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes. An artificial neural it is the layer which is responsible for extracting the required feature from the input data.

2.3 Neuron with Vector Input

A neuron with a single R- element input vector shown below:

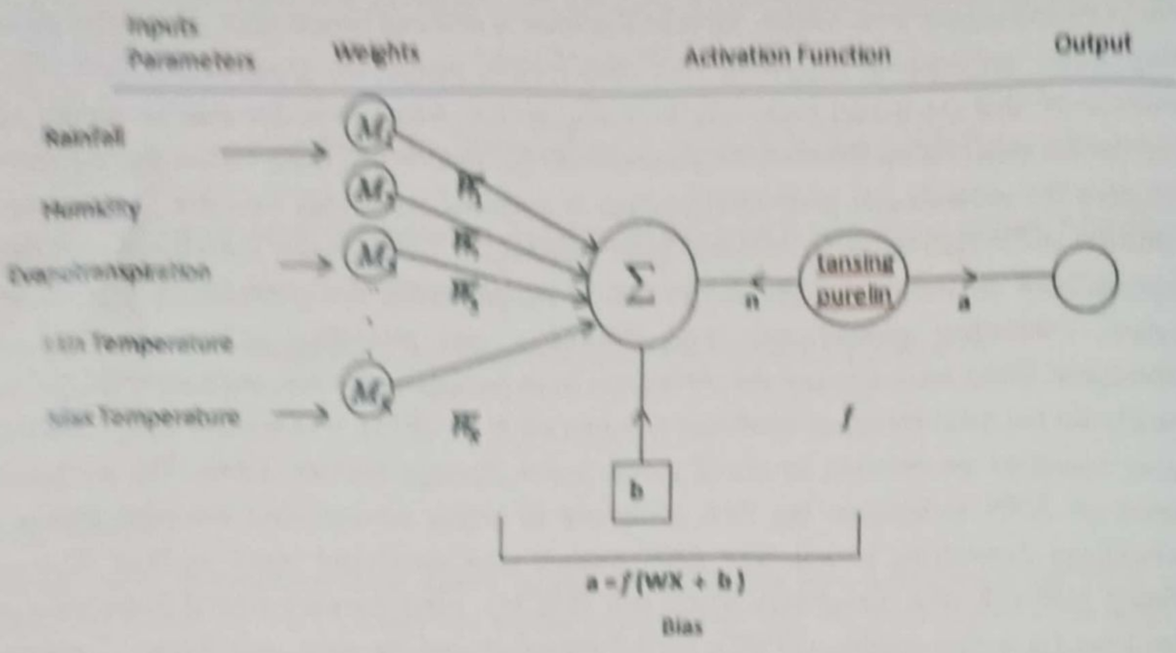

Figure 1 Graphical representation of ANN neuron

The individual element inputs $M_1, M_2, M_3 \ldots\ldots\ldots M_R$ are multiplied by the weight $W_{11}, W_{12}, W_{13} \ldots\ldots\ldots\ldots W_{1,R}$ and the weight values are fed to summation junction, The sum is simply $W \times M$, the dot product of the single row matrix Wand the vector M. The neuron a bias b which summed with the weighted input to form the net input n. this sum n is the argument of the transfer function f.

$$n = W_{11} M_1 + W_{12} M_2 + \ldots\ldots\ldots\ldots, + W_{1,R} M_R + b \qquad 1$$

The Levenberg - Maquadt algorithm was developed by Kenneth Levenberg and Donald Marquadt, provides a numerical solution to the problems of minimizing linear function. The algorithm is fast and has stable convergence. Levenberg – Marquadt algorithm is suitable for training small and medium size problems. The update rule of Levenberg – Marquadt algorithm is:

$$W_{k+1} = W_k \left(J^T J + \mu I\right)^{-1} J_k e_k \qquad 2$$

where,

W = *weight of neural network*

J = *jacobian matrix to be minimize*

μ = *scalar that control the leaning process*

Artificial neural network with feed-forward topology is called feed-forward artificial neural network and as such has only one condition: information must flow from input to output in only one direction with no back-loops.

3.0 Model Application

Water Balance equation is given as difference between inflow and outflow which is equal to changes in aquifer storage. Water balance equation is given as:

$$I = O \pm S\frac{dh}{dt} \tag{3}$$

Where,
I = Rainfall (input)
O = Evapotranspiration (output)
$\frac{dh}{dt}$ = Change in groundwater level with t
$S = Storavity$
$S\frac{dh}{dt} = Storage\ change\ of\ groundwater$ with t

For period without recharge, the groundwater level is expressed as:

$$\frac{dh}{dt} = c(h - h_0) \tag{4}$$

where,
$h = groundwater\ level$
$h_0 = s\tan dard\ groundwater\ level$
$c = cons\tan t$

$$\int \frac{dh}{c(h - h_0)} = \int dt \tag{5}$$

$$h - h_0 = e^{a}e^{ct} \tag{6}$$

$$h = h_0 + Be^{ct} \tag{7}$$

Considering the period of dry season under which our research is based, we adopt equation (7) and the computation of equation (7) is done using five climatic data: relative humidity, maximum and minimum temperature, solar radiation.

We employed Mean Square Error (MSE) and correlation coefficient as criteria to Simulate. Mean Square Error is difference between the observed and computed values, the lower the MSE the more precise the simulation.

$$MSE = \frac{\sum_{1}^{N}\left(y_i - y_i\right)^2}{N} \tag{8}$$

where,

$y = observe\ data$

$\bar{y} = computed\ data$

$N = number\ of\ observation$

Correlation Coefficient between network result and network target outputs in fifteen training, testing and validation groups were used and estimated as:

$$R = \sqrt{1 - \frac{\sum_1^N \left(y_i - \bar{y}_i\right)^2}{\sum y_i^2 - \frac{\sum \bar{y}_i^2}{N}}} \tag{9}$$

4.0 Results and Discussion

In this paper, we presented the data used for a Mathematical model for prediction of quantity of groundwater water allocation system in Mokwa, the resulting outputs and the graphical interpretation of the models. Computational results are performed using Intel® Pentium® Dual T3200@4.00GH 500MBMemory and MATLAB 7.9

The Network Topology, including the number of functional layers and the number of nodes, in each layer, affects the generalization capability and prediction accuracy of the neural networks. The same network structure results in different outcomes for each training, the reason is that threshold and weights are randomly initialized. The input layer was composed of five neuron nodes; evapotranspiration, relative humidity, maximum and minimum temperature and the output consisted of one neuron nodes, namely, groundwater. During the forward propagation, a neural network receives the sample data and transmits the signal first to the input layer and then output layer after the hidden layer function. If the output results are consistent with the test samples then the network training is terminated otherwise, the weight and threshold are repeatedly modified between each layer depending on the back propagation of the error. Network training is completed when the error of the total samples is less than pre – set accuracy.

The climatic data: Maximum temperature, Minimum temperature, Relative humidity, sunshine hours, Rainfall Solar radiation were obtained from the meteorological station and then used for training and Testing of neural network. The N1 is the number of input neuron in the first hidden layer, N2 is the number of output neuron in the output layer, Epoch is a single pass through the full training set, Learning rate is the loss function of a neural network, R- all is the correlation coefficient, R- training is the ability to learn by Example mean and Mean Square Error (MSE) which is the average squared difference between the estimated values and the actual values

The depth to groundwater for all fifteen networks by various training algorithm are compared. It is observed from the Table 1 that Recurrent Neural Network with Levenberg - Marquardt (RNLM) is the best overall performance for groundwater predicted in Mokwa with Mean

Square Error of 137.96 and the corresponding correlation coefficient of 0.85 and by the Recurrent Neural Network with Resilient Back propagation (RNRP) trained with the same algorithm known as the second best with mean square error (MSE) of 138.79 and corresponding correlation coefficient of 0.80.

Table 1: Neural Network for different algorithm

Neural	N1	N2	Epoch	LR	R-Train	R-Test	R-All	MSE	Data %
FFLM	5	5	100	0.9	0.50	0.63	0.60	141.97	80-20
FFRP	5	5	100	0.9	0.46	0.56	0.59	148.04	80-20
FFSCG	5	5	100	0.9	0.53	0.63	0.62	144.08	80-20
FFBFG	5	5	100	0.9	0.60	0.67	0.70	139.85	80-20
FFCGF	5	5	100	0.9	0.61	0.63	0.54	145.60	80-20
RNLM	5	5	100	0.9	0.73	0.78	0.85	137.96	80-20
RNRP	5	5	100	0.9	0.70	0.78	0.80	138.79	80-20
RNSCG	5	5	100	0.9	0.52	0.56	0.59	146.92	80-20
RNBFG	5	5	100	0.9	0.49	0.53	0.61	141.74	80-20
RNCGF	5	5	100	0.9	0.54	0.60	0.60	143.51	80-20
CFLM	5	5	100	0.9	0.40	0.47	0.51	145.84	80-20
CFRP	5	5	100	0.9	0.45	0.57	0.50	146.10	80-20
CFSCG	5	5	100	0.9	0.51	0.50	0.56	144.59	80-20
CFBFG	5	5	100	0.9	0.50	0.56	0.60	140.21	80-20
CFCGF	5	5	100	0.9	0.61	0.54	0.62	142.63	80-20

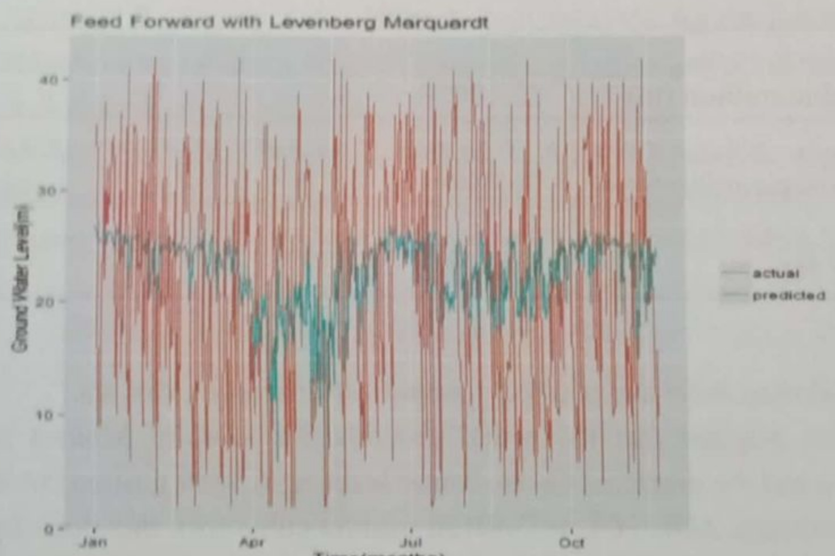

Figure 1: Hydrograph for Feed Forward Levenberg marquardt

Figure 1 shows the hydrograph of groundwater level (m) against time (month) in Mokwa, it is observed from the graph that the Feed Forward Levenberg Marquadt Simulation are closer to the corresponding observed values, the depth to groundwater increases from `December and reached its highest level in April and reached its lowest in September.

Figure 2 shows the hydrograph of groundwater level (m) against time (month) is observed from the graph that the Feed Forward with Resilient Back propagation is the second best algorithm that predicted groundwater levels, the depth to groundwater increases from December and reached its highest level in April and reached its lowest in September.

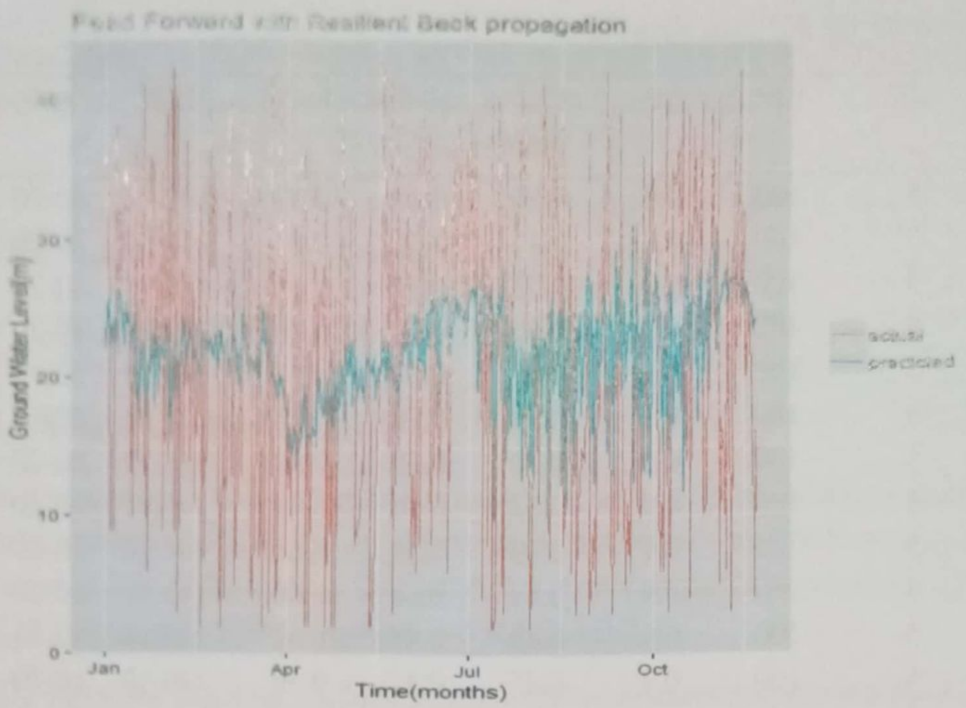

Figure 2: Hydrograph for Feed Forward with Resilient Back propagation

Table 2: Actual Groundwater level and Groundwater Predicted Level in Mokwa

Actual Groundwater Level cubic million (m)	27.19018
Predicted Groundwater Level cubic million (m)	26.7889
Difference between AGL and PGL	0.40128

Table 2 shows the actual groundwater level and predicted groundwater level in Mokwa. The Simulation results analysis Suggest that the actual groundwater level in Mokwa is 27.19018 million cubic m/ 15ha and the predicted Groundwater level is 26.7889 million cubic m/15 ha while the difference between AGL-PGL is 0.40128 million cubic (m). this done by finding average mean from the ground water data.

4.0 CONCLUSION

In this research, we analysed the ANNs model with various network to simulate water level fluctuation. The effect of various algorithms was studied and analysed, ANNs computing is considered as a successful technique to apply for monthly groundwater level simulation from the available data. Levenberg - Marquardt (RNLM) is the best overall performance for groundwater predicted in Mokwa with Mean Square Error of 137.96 and the corresponding correlation coefficient of 0.85 and by the Recurrent Neural Network with Resilient Back propagation (RNRP) trained with the same algorithm known as the second best with mean square error (MSE) of 138.79 and corresponding correlation coefficient of 0.80. The Simulation results analysis revealed that the actual groundwater level in Mokwa is 27.19018 million cubic m/ 15ha and the predicted Groundwater level is 26.7889million cubic m/15 ha while the difference between AGL-PGL is 0,40128. The obtained results from the study area were acceptable and confirmed that artificial simulation tool to employ in the area of groundwater hydrology

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