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ORIGINAL ARTICLE

Prediction of groundwater level in basement complex terrain using artificial neural network: a case of Ijebu-Jesa, southwestern Nigeria

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Abstract

Empirical relationship between geoelectric parameters and groundwater level in boreholes/wells has not been established. Also, prediction of groundwater level from geoelectric parameters had hitherto not been reported. In order to overcome these challenges, the capability of artificial neural network (ANN) to model nonlinear system was explored in this study to predict groundwater level from geoelectric parameters. To achieve the above objectives, the ground water level (GWL) of all the accessible wells in the study area was obtained and this was used as the output parameter for the ANN model. A total of fifty-one (51) parametric vertical electrical soundings (VES) stations were occupied at each of the well location by adopting Schlumberger array configuration with electrode spacing (AB/2) ranging from 1 to 100 m. The VES data were quantitatively interpreted to generate geoelectric parameters believed to be controlling the groundwater flow and storage in the area. These parameters served as input for ANN model. The capability of ANN as a nonlinear modeling system was thereafter applied to produce a model that can predict the GWL from the input parameters. The efficiency of the model was evaluated by estimating the mean square error (MSE) and the regression coefficient (R) for the model. The results established that seasonal variation has little effect on the water fluctuation in the wells. Two aquifer types, weathered and fractured basement aquifer types, were delineated in the area. The results of the ANN model validation showed low MSE of 0.0014286 and the high regression coefficient (R) of 0.98731. This indicates that ANN can be used to predict GWL in a basement complex terrain with reasonably good accuracy. It is concluded that the ANN can effectively predict GWL from geoelectric parameters.

Keywords Electrical resistivity · Schlumberger array · Artificial neural network · Prediction model

Introduction

Water is the elixir of life and is crucial for sustainable development. Earlier, it was considered to be a limitless or at least fully renewable natural resource. However, in the last 20 years or so, there has been a tremendous pressure on this precious natural resource mainly due to rapid industrialization and human population. This is because an increase in the human population will simply result in increasing the demand for irrigation purpose to meet food production requirements. Though, the advancement in agricultural technology has been impressive in many regions, poor irrigation management has resulted in considerable depletion of the groundwater table, damaged soils and deterioration in the water quality thus making the availability of water in the future highly uncertain. Keeping in mind the scarcity of available water resources in the near future and its impending threats, it has become imperative on the part of water scientists as well as planners to quantify the available water resources for its judicial use. Thus, a ready reckoner to monitor the fluctuations in groundwater levels well in advance is the need of the hour to devise sustainable water management protocols (Sreekanth et al. 2009).

Due to the reliability and sustainability of the resource, groundwater has been generally accepted to be the best

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quality source of water for both drinking and irrigation purposes around the world (Hoque et al. 2009; Adiat et al. 2012). This, in addition to social development and agricultural production, has led to an increase in the awareness on the need to utilize and explore groundwater resources as alternative sources of water supply (Abdul et al. 2001).

Groundwater is reserved in the subsurface in a geologic system called aquifer. Groundwater level is an indicator of groundwater availability, groundwater flow and the physical characteristics of an aquifer or groundwater system (Nair and Sindhu 2016). A decrease in groundwater levels can trigger a number of eco-environmental problems capable of seriously affecting both local agricultural production and economic development (Li et al. 2019). Groundwater level is an important indicator of groundwater balance. Influence of climatic factors and human activities can make groundwater level exhibits cyclical and random characteristics. Therefore, the accurate prediction of groundwater level is of great significance for the rational utilization of groundwater resources and the sustainable development of the social economy (Li et al. 2019).

Electrical resistivity geophysical prospecting technique has been extensively utilized by many researchers in various domains of groundwater studies (Adiat et al. 2013). For instance, vertical electrical sounding (VES) technique can significantly contribute to the accurate location of aquifer not only through the development of its geometry (Zakari et al. 2015) but also by establishing relationship between the hydrogeological and geoelectrical parameters (Adiat et al. 2013).

An understanding of groundwater dynamics with the application of computer and mathematical tools can be used to predict groundwater flow and level fluctuation (Mao et al. 2002). In this direction, several studies were carried out for forecasting the groundwater levels using conceptual/physical models that are not only laborious, but also have

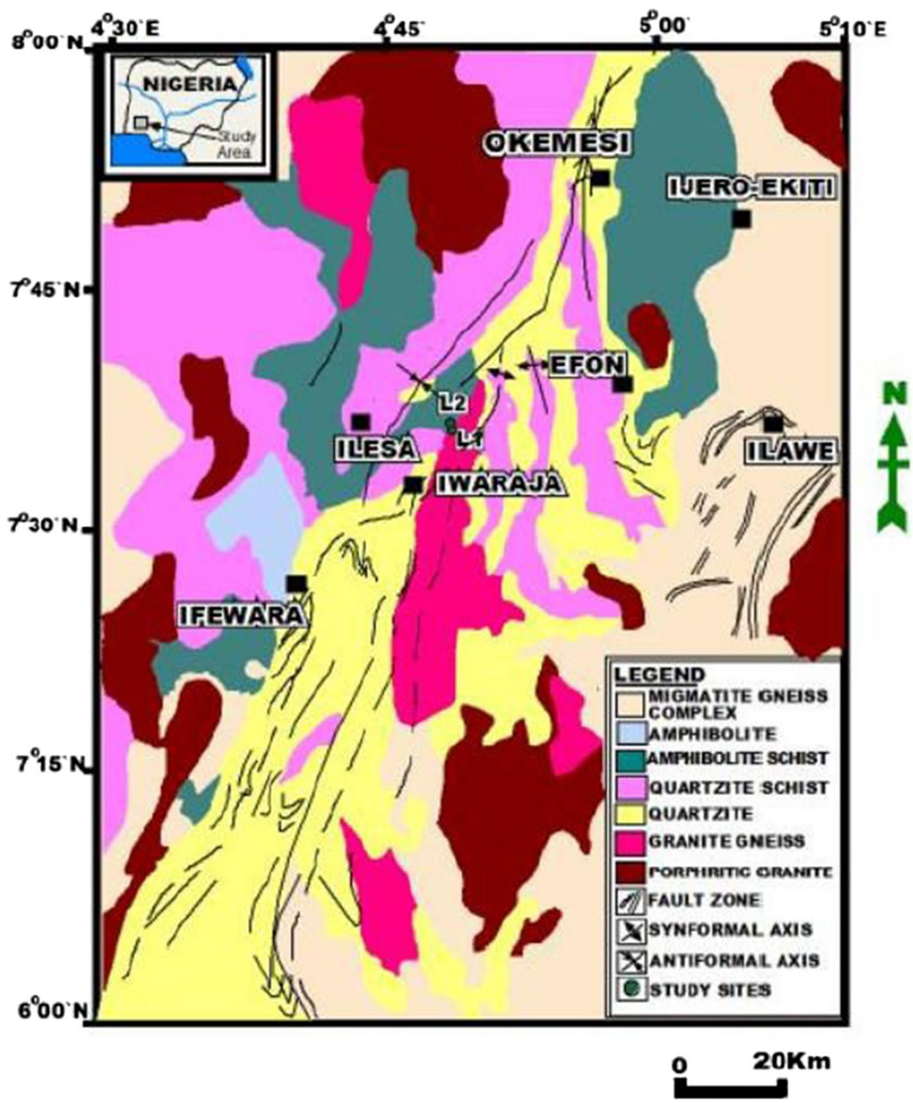

Fig. 1 Regional geological map of Okemesi Fold Belt showing study area (adapted from Odeyemi 1993)

practical limitations (Daliakopoulos et al. 2005; Lallahem et al. 2005a, b) as many inter-related variables are involved. In the recent past, soft computing tools like artificial neural networks (ANNs) have been used increasingly in various fields of science and technology for prediction purposes (Brion et al. 2002). In particular, ANNs have been found useful in the area of groundwater modeling.

The ANN is a general-purpose model with a limited set of variables and is used as a universal functional approximator (Hornik 1991). It can forecast many nonlinear time series events (Hill et al. 1996; Tang and Fishwick 1993; Zhang 2003) over conventional simulation methods (French et al. 1992). Basically, ANNs are intelligent systems that are related in some way to a simplified biological model of the human brain. They are composed of many simple elements called neurons operating in parallel and connected to each other in the forward path by some multipliers called connection weights. Usually, ANNs are trained by adjusting the values of these connection weights between the network elements. ANNs have applications in various fields like forecasting, system identification, pattern recognition, classification, speech recognition, image processing, etc. Many studies on various aspects of groundwater studies have adopted ANN as a research tool. Such aspects of groundwater studies include, but not limited to, groundwater remediation (Gumrah et al. 2000; Zhao et al. 2007; Yan and Minsker 2006), subsurface characterization (Parkin et al. 2007), groundwater pollution (Gemitzi et al. 2009; Coppola et al. 2007) and parameter estimation (Aziz and Wong 1992; Ajmera and Rastogi 2008).

Simulation of karstic and leaky aquifers (Coppola et al. 2003), fluctuation of alluvial aquifer groundwater level (Esmaili 2003), evaluation of dynamic water level in karstic aquifer (Lallahem et al. 2005a, b), simulation of the effects of hydrological, weather and humidity conditions on groundwater level (Shaouuan et al. 2007), etc., has been carried out

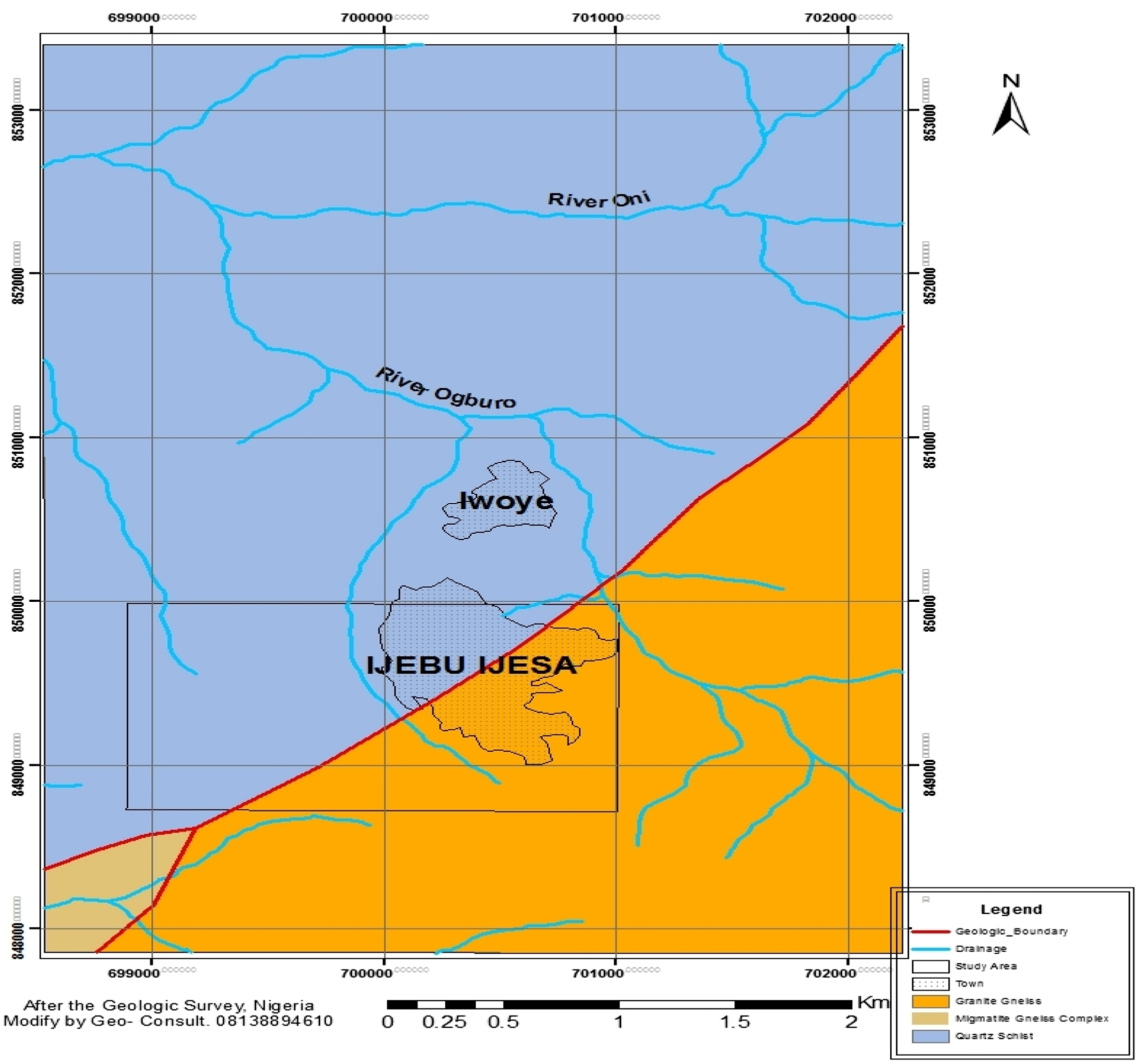

Fig. 2 Local geological map of the study area (modified after the Geologic Survey, Nigeria)

by researchers around the world. It is, however, observed, within the context of literature review done for this study, that empirical relationship between geoelectric parameters and groundwater level has not been established in the literature. Furthermore, prediction of groundwater level from geoelectric parameters still remains a challenge that has hitherto not been carried out. More importantly, the capability of ANN has not been employed in this aspect of groundwater study in the study area. In order to overcome this challenge, an attempt would be made in this study to adopt ANN as a tool to predict groundwater level from geoelectric parameters. In addition to the attainment of the above aim, the study was also carried out to achieve the following objectives:

1. generate geoelectric parameters of hydrogeological importance;
2. produce piezometric head parameters;
3. establish nonparametric relationship between the input data, i.e., geoelectric parameters and groundwater level (i.e., the output) in the study area;
4. develop ANN and validate model for predicting groundwater column in basement complex terrain.

Description of the study area

The study area is Ijebu-Jesa, the capital of the Oriade Local Government Area of Osun state, southwestern Nigeria. It falls between latitude 7° 40′ N and 7° 43′ N and longitude 4° 48′ E and 4° 50′ E. The topography of the area is gently undulating. The climate is well defined with wet and dry seasons with annual rainfall varying between 150 and 200 cm. The annual relative humidity is over 80% with temperature ranging from 24 to 27 °C. The vegetation of the area is of rain forest.

The study area falls within the basement complex of the southwestern Nigeria. It forms part of the African crystalline shield which consists predominantly of migmatite and undifferentiated gneisses and quartzite (Rahaman 1976). The important structural features in the basement rocks include joints, faults, fractures, lineations and geological boundaries. These structural features are relevant in the control of groundwater accumulation and movement.

The major rock associations of this area form part of the Proterozoic Ilesha schist belt in southwestern part of Nigeria. This is predominantly developed in the western half of the country. In terms of structural features, lithology and

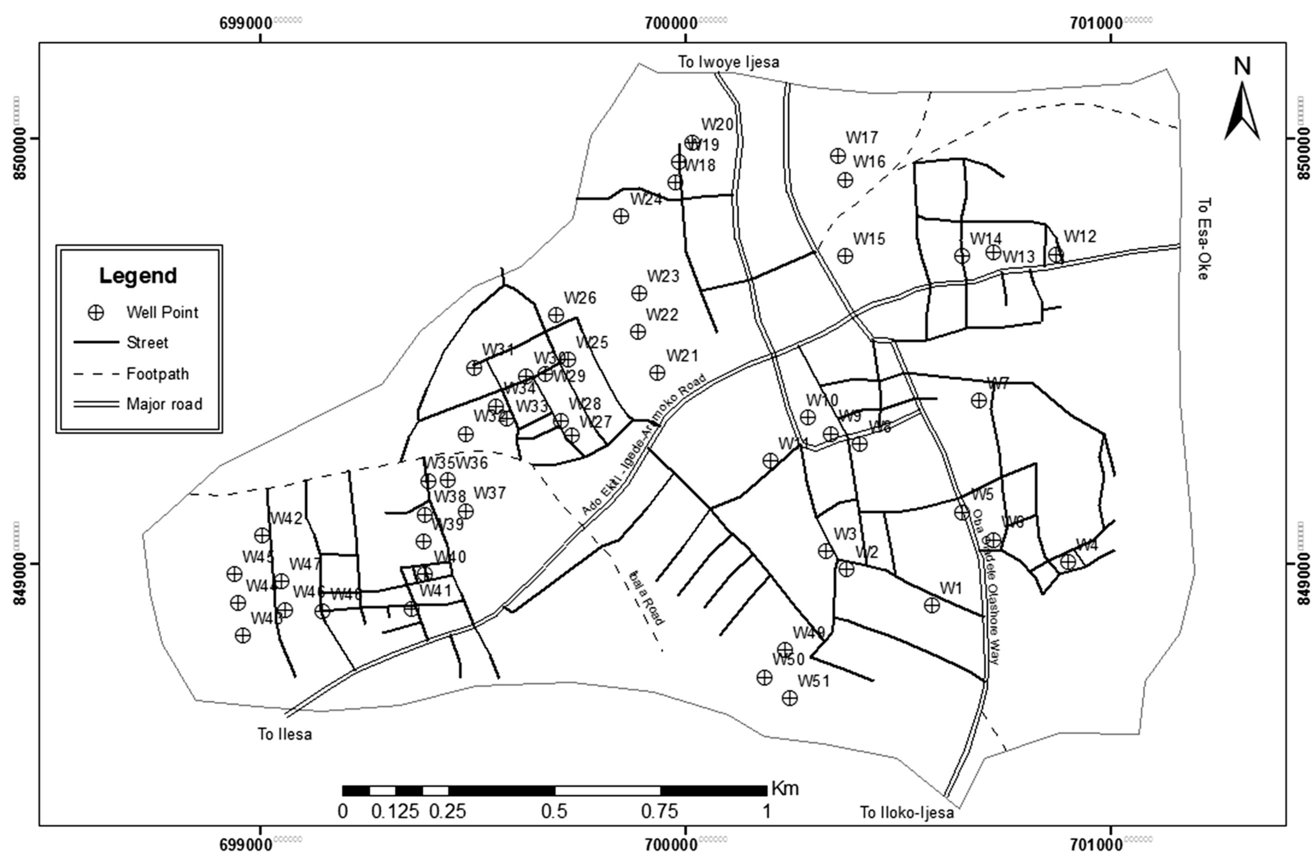

Fig. 3 Base map of the study area showing well/VES locations

mineralization, the schist belts of Nigeria show considerable similarities to the Achaean green stone belts (Olusegun et al. 1995). However, the latter usually contain much larger proportions of mafic and ultramafic bodies and assemblages of lower metamorphic grade (Olusegun et al. 1995; Ajayi and Ogedengbe 2003).

Rocks in the Ilesha schist belt are structurally divided into two main segments by two major fracture zones often called the Iwaraja faults in the eastern part and the Ifewara faults in the western part (Elueze 1986; Folami 1992; Kayode 2006). The regional geological map showing the study area is shown in Fig. 1. The northern part of the fault comprises mostly of amphibolites, amphibole schist, meta-ultramafic and meta-pelites. Extensive psammitic units with minor meta-pelite constitute the eastern segment (Rahaman 1976). These are found as quartzite and quartz schist. All these assemblages are associated with migmatitic gneisses and are cut by a variety of granitic bodies (Rahaman 1976; Elueze 1986; Olusegun et al. 1995; Ajayi and Ogedengbe 2003).

The rocks of the Ilesha district may be broadly grouped into gneiss–migmatite complex, mafic–ultramafic suite (or amphibolites complex), meta-sedimentary assemblages and intrusive suite of granitic rocks. A variety of minor rock types are also related to these units. The gneiss–migmatite complex comprises migmatitic and granitic, calcareous and granulitic rocks. The mafic–ultramafic suite is composed mainly of amphibolites and amphibole schist and minor meta-ultramafites, made up of anthophyllite–tremolite–chlorite and talc schist (Rahaman 1976).

The meta-sedimentary assemblages, chiefly meta-pelites and psammitic units, are found as quartzite and quartz schist. The intrusive suite consists essentially of Pan African (c. 600 Ma.) granitic units. The minor rocks include garnet–quartz–chlorite bodies, biotite–garnet rock, syenitic bodies and dolerites (Olusegun et al. 1995; Folami 1992, Rahaman 1976).

The Ijebu-Jesa segment of the Ilesha schist belt falls into the migmatite–gneiss group with meta-sedimentary assemblages chiefly found as quartz schist. The quartz schist was mainly exposed by erosion within the study area (Fig. 2).

Methodologies

The study was executed in three phases which were groundwater level measurements, geophysical survey and prediction of groundwater level using ANN. The detail descriptions of methodology used in each of the phases are presented in "Groundwater level measurements"–"Prediction using artificial neural network (ANN)" sections below.

Groundwater level measurements

A total number of fifty-one (51) wells were accessible in the study area. The well location is shown in Fig. 3. The static water level and depth to the bottom of each well were determined at the peaks of dry and raining seasons and mean values obtained from the values obtained from the two seasons. In order to justify the use of the mean value used for the data obtained for the two seasons, reliability of the mean was statistically examined by carrying out some measures of dispersion which include the range and mean deviation. The coefficient of variation (CV), (the ratio of the standard deviation to the mean), was also determined to further ascertain the level of dispersion, occasioned by seasonal variation, on the values obtained in the two periods. The ground water level (GWL) was thereafter obtained from the two measured values.

Geophysical survey

The vertical electrical resistivity (VES) data were acquired using the Ohmega Terrameter and its accessories. A total of fifty-one (51) VES stations were occupied at each of the

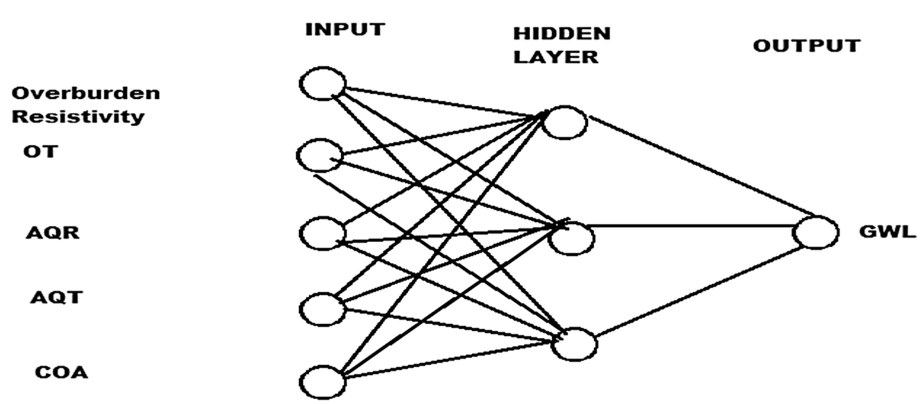

Fig. 4 Schematic diagram of the ANN architecture used for the study

well location as shown in Fig. 3 (i.e., parametric VES). The Schlumberger array was adopted with electrode spacing (AB/2) ranging from 1 to 100 m. The coordinates of measurement station were taken using Garmin GPS 7.0. The VES data acquired were processed qualitatively and quantitatively. The qualitative analysis involved mere inspection of the curve for its type; the quantitative analysis on the other hand involved partial curve matching to generate geoelectric parameters that served as initial model parameters for subsequent computer iteration.

The information obtained from the results of the interpretation of the VES data was utilized to estimate the geoelectric parameters [aquifer resistivity (AQR), aquifer thickness (AQT), overburden resistivity (OR), overburden thickness and (OT) and coefficient of anisotropy (COA)] that were used as input parameters to develop the artificial neural network (ANN) model.

Prediction using artificial neural network (ANN)

Steps of the artificial neural network (ANN) as adopted in the study:

The final stage of the methodology was the implementation of the artificial neural network. Neural Network Toolbox in MATLAB Version (8.3) 2015 was used. A back projection based feed forward neural network was used to model the input and output parameters using MATLAB neural network toolbox. The procedural steps involved the following: parameters/variables selection, ANN architecture development, data processing and the model performance evaluation.

Parameters/variables selection

Five parameters [i.e., overburden resistivity (OR); aquifer resistivity (AQR); overburden thickness (OT), aquifer thickness (AQT)] and coefficient of anisotropy (COA) were used as the input parameters while the measured groundwater level (GWL) was the model output.

Data processing

Data preprocessing involves partitioning of the data into three sets which were the training, validation and testing sets in the ratio: 70:15:15, respectively. The training set was the largest set used by neural network to learn patterns present in the data. The 70% training set was selected randomly across the range of the whole data so as to ensure that the data contain sufficient representation of the patterns. This will enable the network to mimic the underlying relationship between input and output variables adequately. In order to shuffle the data, the training data were presented to the network in random order so as to ensure that the response of the training network will not vary with the order of pattern presentation (Manisha et al. 2008). Training was controlled by some conditions such as: the maximum number of iterations, target performance which specifies the tolerance between the neural network prediction and actual outputs, the maximum run time and the minimum allowed gradient. The desired results were generated in the output layer. The network achieves the desired learning by adjusting its interconnected weights continuously until there was a close match between the output from the neurons and the output from the training data. The difference between the predicted outputs and the original outputs is referred to as error. At the end of the training phase, the neural network correctly reproduced the target output values for the training data provided with minimal error. 15% of the data was used for testing, whereas the remaining 15% was allocated for model validation. The validation set was used to make a final check on the performance of the trained network after the completion of the training/testing processes. Validation set is an independent data set which was not used during training process. Performance criteria adopted in this study were mean square error (MSE) and regression coefficient (R).

ANN architecture development

The architecture of neural network defines its structure. It is the most important part of ANN development. Different neural network architectures were developed in order to establish a relationship between the input and output. All the networks were of the feed forward type. An ANN consists of input, hidden and output layers as shown in Fig. 4. The network architectures were trained by varying the number of hidden layer and then by varying number of neurons in each hidden layer.

The process involves determining the number of input neurons, the number of output neurons, the number of hidden layers and number of neurons in the hidden layers. Since the numbers of input and output neurons are decided by the nature of the problem, the number of hidden layer and associated hidden neurons represent the major decision to be made in overall architecture design.

In order to simplify the network architecture and thus reduce computational effort, a single layer network was adopted. In addition to this, it has been established that a single layer feed forward network with sufficient neurons can adequately approximate any nonlinear function (Haykin 1999; Hornik 1991). Starting with two neurons and then increasing the number while monitoring the performance criteria for each resulting architecture each time, the training was carried out until there was no significant

Table 1 Results of the groundwater level measurement

Well no.	Peak dry season SWL (m)	Peak raining season SWL (m)	Average SWL (m)	Well depth (m)	Groundwater level (GWL) (m)
1	10	10.8	10.4	11.3	0.9
2	5.3	5.9	5.6	7.4	1.8
3	8.8	9.5	9.15	10.2	1.05
4	9.5	10.6	10.05	11.3	1.25
5	9.6	10.6	10.1	11.8	1.7
6	11.1	11.9	11.5	13.2	1.7
7	10.2	10.7	10.45	11.9	1.45
8	10.3	10.9	10.6	12.8	2.2
9	9.2	9.9	9.55	11.4	1.85
10	12	13.1	12.55	14.3	1.75
11	9.8	9	9.4	11.2	1.8
12	7.5	8.4	7.95	9.9	1.95
13	9.4	9.7	9.55	10.2	0.65
14	8.3	8.4	8.35	10.6	2.25
15	3.6	3.7	3.65	8.3	4.65
16	7.2	9	8.1	10.7	2.6
17	8.2	9.1	8.65	11.9	3.25
18	11	11.6	11.3	13.9	2.6
19	10.2	10.8	10.5	12.6	2.1
20	8.1	8.8	8.45	10.3	1.85
21	4.5	5.1	4.8	6.2	1.4
22	5.1	5.5	5.3	6.8	1.5
23	5.1	5	5.05	6.5	1.45
24	6	6.7	6.35	7.5	1.15
25	6.5	6.7	6.6	8	1.4
26	5.3	5.4	5.35	7	1.65
27	9.1	9.7	9.4	10.9	1.5
28	9.7	10.5	10.1	11.6	1.5
29	10.6	11.5	11.05	12.5	1.45
30	10.8	11.9	11.35	12.9	1.55
31	8.9	9.6	9.25	14.1	4.85
32	8.9	9.4	9.15	13.7	4.55
33	10.9	11.1	11	12.6	1.6
34	11.6	12.4	12	13.1	1.1
35	10.5	10.9	10.7	12.8	2.1
36	10.6	10.8	10.7	12.5	1.8
37	11.7	11.9	11.8	13.6	1.8
38	10.9	11.6	11.25	12	0.75
39	9.6	10.7	10.15	13.4	3.25
40	9.8	10.1	9.95	13.6	3.65
41	8.2	8.4	8.3	10.9	2.6
42	8.9	10.3	9.6	12.7	3.1
43	6.5	6.8	6.65	9.8	3.15
44	7.5	8.1	7.8	10.6	2.8
45	6.9	7.6	7.25	10.5	3.25
46	8.7	9.4	9.05	11.8	2.75
47	10.5	10.9	10.7	12.6	1.9
48	10.2	10.6	10.4	13.5	3.1
49	7.5	7.7	7.6	10.7	3.1

Table 1 (continued)

Well no.	Peak dry season SWL (m)	Peak raining season SWL (m)	Average SWL (m)	Well depth (m)	Groundwater level (GWL) (m)
50	7.9	9	8.45	11.2	2.75
51	7.6	9.1	8.35	11.5	3.15

improvement in the error. In order to objectively evaluate the model performance, the mean square error (MSE) and regression coefficient (R) were computed and are summarized.

Model performance evaluation

In order to assess the efficiency of the artificial neural network model, it was validated with 15% of the field data. The five parameters (i.e., OR, AQR, OT, AQT and COA) for all the validation data set represent the input parameters. These input parameters were put into the ANN model. The model separately simulated the input data to produce the output groundwater level (GWL). The model outputs (P_j) were compared with the expected outputs (T_j) (i.e., output from the field data measured). The efficiency of the model was determined by estimating the mean square error (MSE) and the regression coefficient (R) for the model.

Results and discussions

Results of the groundwater level measurements

The results of the measurements obtained from the wells/boreholes are presented in Table 1. The value of the coefficient of variation (CV) as determined from the results shown on Table 1 is 0.2% while the range varies from − 0.8 to 1.5. The small values obtained for both the CV and the range are an indication that the dispersion is small suggesting that seasonal variation has little effect on the water fluctuation in the wells and this further justifies the use of average of the two values. The groundwater level (GWL) shown in the last column of Table 1 was used as the output parameter for the ANN model.

Results of the geophysical survey

The geoelectric parameters obtained from the results of the interpretation of the VES are presented in Table 2. The geoelectric sections developed from results of the interpretation of the VES revealed that the subsurface is largely characterized by a maximum of between three and four layers. These layers are the top soil, the weathered basement, the fractured basement layer and the fresh basement. The weathered and or the fractured basement constitute the aquifer in the area. In other words, weathered basement aquifer and fractured basement aquifer are the aquifer types obtainable in the area. It is also observed that all the wells/boreholes in the area tap water from the delineated aquifer, this thus suggests that there is justification for predicting groundwater level from the geoelectric parameters obtained from the results of parametric soundings carried in the study area. The parameters shown in Table 2 were used as the input parameters for the ANN model.

Results of the ANN parameters selection

Five parameters, OR, AQR, OT, AQT and COA, shown in Table 2 were selected and used as the input parameters for the ANN model. These five parameters had been established to be significantly controlling the flow and accumulation of groundwater in the basement complex terrain and particularly in the study area (Adiat et al. 2018).

Results of the ANN data processing/ANN architecture development

The parameters shown in Table 2 are randomly partitioned into three in the ratio 70:15:15 to represent training, testing and validation data, respectively.

The results of performance evaluation of several networks trained were compared. It was observed that the number of iterations required by each network architecture differs. This implies that the number of iterations required by each network architecture to converge is not constant and this accounts for different iteration numbers recorded for different architecture (Table 3).

The effect of network architecture on its performance is displayed in the table. No appreciable improvement was accomplished by the addition of extra neuron into the network before or after 22 hidden neurons.

Network with 22 hidden neurons gave the best validation performance values of 0.24903, 0.99998, 0.95223 and 0.98731 for regression coefficient (R), training, testing and validation, respectively. The closeness of the R value to 1 is an indication that both the predicted output (i.e., model output) and the expected output (i.e., the output used for the simulation) are well fitted.

Table 2 Geoelectric parameter for ANN input and output

Well no.	ANN input					ANN output
	OR	OT	AQR	AQT	COA	GWL
1	49	3	150	12.2	1.09	0.9
2	73	0.5	43	10.2	1.01	1.8
3	38	1.7	132	18.1	1.06	1
4	677	3.5	191	9.4	1.17	1.2
5	93	2.5	311	22	1.23	1.7
6	425	0.5	215	15.1	1.01	1.7
7	303	1.7	79	33.3	1.08	1.4
8	32	0.4	52	10.6	1	2.2
9	55	2.4	75	20.5	1.05	1.8
10	115	12.6	50	7.4	1.13	1.7
11	99	11.4	117	10.6	1.04	1.8
12	63	0.6	56	16.7	1	1.9
13	98	3.4	103	20.1	1.03	0.6
14	73	4	82	26.1	1.01	2.2
15	54	3.1	138	15	1.24	4.6
16	275	4.9	115	16.5	1.2	2.6
17	169	5.3	92	14.3	1.11	2.2
18	102	11.2	85	36.2	1.06	2.6
19	213	15.2	47	19.1	1.33	2.1
20	215	5.4	34	18.8	1.92	1.8
21	99	2.1	95	18	1	1.4
22	71	0.8	144	3.4	1.03	1.5
23	567	0.7	265	35.9	1.01	1.4
24	474	6	129	20.2	1.27	2.1
25	121	0.5	254	17.2	1.01	1.4
26	358	20.9	61	18.1	1.02	1.6
27	90	3.1	23	3.9	1.24	1.5
28	51	10.3	145	11.9	1.26	1.5
29	404	8.9	167	12.6	1.28	1.4
30	349	3.5	260	22.7	1.03	1.5
31	100	0.4	294	1.7	1.09	4.8
32	710	6	649	2.4	2.64	4.5
33	76	0.5	82	1.7	1	1.6
34	135	17.1	143	18.8	1.04	1.1
35	734	11.6	347	50.9	1.19	2.1
36	946	30.3	312	48.2	1.37	1.7
37	157	2.4	49	49.1	1.06	1.8
38	262	4	102	15.1	1.18	0.7
39	821	13.4	229	40.2	1.61	3.2
40	1426	31.4	387	43.5	1.13	3.6
41	608	15	382	41.6	1.11	2.6
42	467	5	123	23.7	1.29	3.1
43	598	15.5	510	28.1	1.1	2.1
44	81	0.4	83	1.6	1	2.8
45	112	0.4	204	1.8	1.03	3.2
46	187	0.4	161	5.9	1	2.7
47	1083	12.9	289	38	1.32	1.9
48	131	2.6	13	14.9	1.43	3.1
49	207	0.7	137	3.8	1.62	3.1

Table 2 (continued)

Well no.	ANN input					ANN output
	OR	OT	AQR	AQT	COA	GWL
50	1528	7.9	228	12.1	1.78	2.7
51	138	2.6	570	19.1	1.11	3.1

Table 3 Summary of performance evaluations of ANN architectures

Network architecture	Best validation performance	Regression (*R*) for training set	Regression (*R*) for testing	Regression (*R*) for validation set	Regression for all	No. of iteration	No. of iteration at best validation performance
Net 1 [2]	2.2722	0.99988	0.88445	0.76175	0.95592	10	4
Net 1 [4]	2.7091	0.99998	0.9654	0.86818	0.97183	12	6
Net 1 [6]	4.1692	0.99999	0.80165	0.8659	0.94508	17	11
Net 1 [8]	1.2842	0.99999	0.89737	0.94787	0.96579	19	13
Net 1 [10]	6.1707	0.99999	0.0912	0.86232	0.94561	9	3
Net 1 [12]	0.4430	1	0.87559	0.97646	0.97688	23	17
Net 1 [14]	0.47164	1	0.7688	0.97842	0.96154	72	69
Net 1 [16]	8.8022	0.99999	0.72823	0.51562	0.87995	9	3
Net 1 [18]	0.46045	0.99774	0.83706	0.97405	0.9527	7	1
Net 1 [20]	1.1959	0.99999	0.95982	0.92252	0.9773	22	16
Net 1 [22]	0.24903	0.99998	0.95223	0.98534	0.98731	11	5
Net 1 [28]	4.8064	0.99792	0.91356	0.66195	0.93569	7	1
Net 1 [30]	1.9216	0.99999	0.79642	0.95931	0.95639	34	28

Apart from the best performance in terms of MSE and *R*, network with 22 neurons provides simpler architecture needed for better computational efficiency when compared to others. Consequently, the network with 5 inputs, 22 hidden neurons and 1 output neuron was selected.

Results of the ANN model performance evaluation

Figure 5 is the regression coefficient (*R*) plot for the best architecture of 22 hidden layers. For training, neural network fits data along the blue line, the actual network outputs plotted in terms of the associated target values and *R* for training is **0.99998** which is high and close to 1. The closeness of the *R* value to 1 is an indication that both the predicted output and the expected output are well fitted. For testing, neural network fits data along the red line, the actual network outputs plotted in terms of the associated target values and *R* for testing is **0.95223**. Validation data fit on the green light with *R* value of **0.98534**. The value of *R* for all training, testing and validation simulated together is **0.98731**. The closeness of the *R* value to 1 is an indication that the model fits the data well with accurate prediction of the groundwater level.

The results obtained from training of the data are presented in Table 4. The outputs generated by the ANN model [i.e., the predicted output (P_j)] as compared with the output used for the model training [i.e., the expected output (T_j)] are shown in the table. The mean square error (MSE) (one of the criteria used to evaluate the effectiveness of the performance of the model is shown in the table while the regression coefficient (*R*) had earlier been presented in Fig. 5).

The validation results for the ANN models are presented in Table 5. The mean square prediction error as shown in the table is 0.0014286 suggesting that the error limit of the prediction accuracy of the ANN model is **0.0014286**. The regression value of 0.98534 was obtained for the ANN model (Fig. 6). The regression coefficient values of **0.98534** obtained for the *ANN* model indicate that the output values of the validation data and the expected output are well fitted in the model. Furthermore, the closeness of the regression value to 1 in the ANN model is an indication that the model is efficient in terms of groundwater level prediction.

High *R* value and small MSE value obtained ANN show that the model fits the data well. The results obtained from analysis of the data clearly showed that ANN model is best fit for predicting the groundwater level. This suggests that model can be applied in other areas of similar geology.

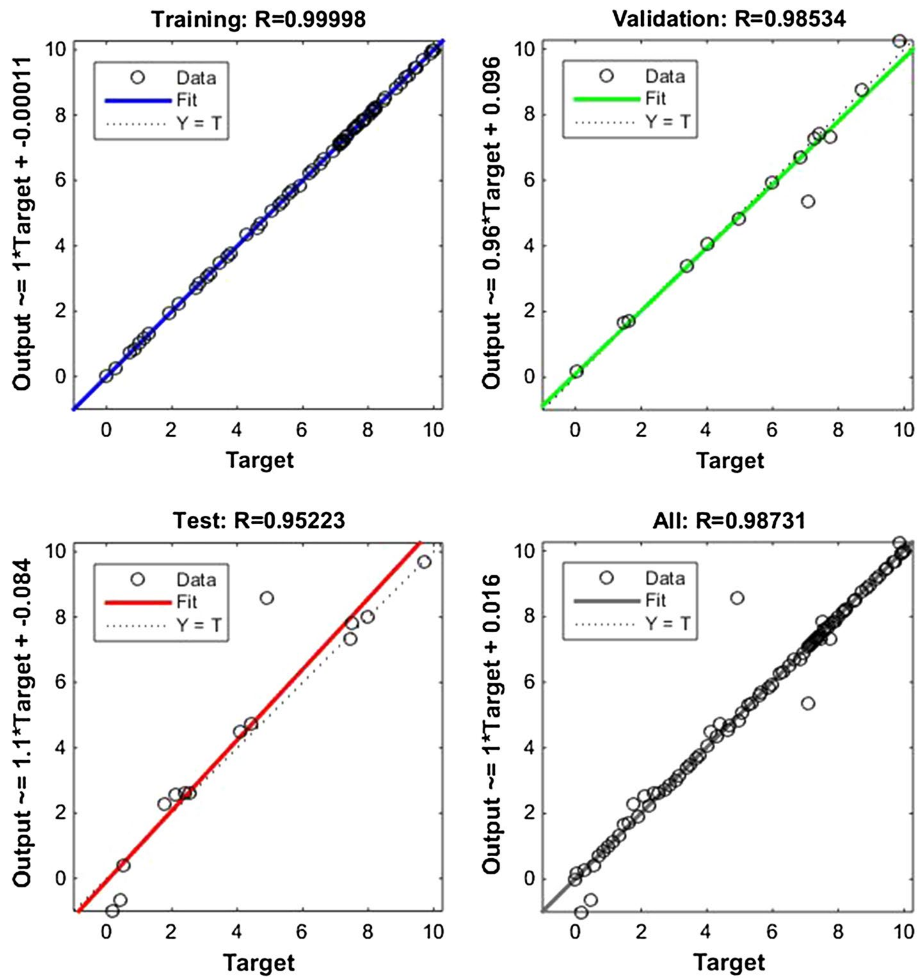

Fig. 5 Regression plot for neural network with 22 neurons (hidden layers)

Conclusion

Prediction of groundwater level (GWL) from geoelectric parameters is still a challenge in groundwater studies. This is partly because the empirical relationship between groundwater level and geoelectric parameters has hitherto not been established. An attempt was made in this study to overcome these challenges by exploring the capability of artificial neural network (ANN) to model nonlinear system.

In order to achieve the objectives of the study, the piezometric head parameters of fifty-one (51) accessible wells in the study area were measured at the peaks of dry and raining seasons. These were used to obtain the GWL in these wells having established that a seasonal variation does not have significant effect on the groundwater fluctuation in the area. The GWL so obtained was used as the output parameter for the ANN model.

A total of fifty-one (51) parametric vertical electrical soundings (VES) stations were occupied at each of the well location by adopting Schlumberger array configuration with electrode spacing (AB/2) ranging from 1 to 100 m. The results obtained from the quantitative interpretation of the VES data were used to generate geoelectric parameters which include aquifer resistivity (AQR), aquifer thickness (AQT), overburden resistivity (OR), overburden thickness and (OT) and coefficient of anisotropy (COA). These parameters had been established to be controlling the groundwater flow and storage in the basement complex terrain and particularly the study area. These geoelectric parameters served as the input parameters for ANN model.

The capability of ANN as a nonlinear modeling system was thereafter applied to produce a model that can predict the GWL from the input parameters. The efficiency of the model was evaluated by estimating the mean square error (MSE) and the regression coefficient (*R*) for the model.

The results established that seasonal variation has little effect on the water fluctuation in the wells. The geoelectric sections developed from results of the interpretation of the VES revealed that the subsurface is largely characterized by a maximum of between three and four layers which are the top soil, the weathered basement, the fractured basement layer and the fresh basement. Two aquifer types (weathered basement aquifer and fractured basement aquifer) are obtainable in the area. It was also established that all the wells/

Table 4 ANN summary table for training data set

Input parameters					Measured GWL output (T_j)	ANN model predicted GWL output (P_j)	Prediction error	Square of prediction error
OR (Ωm)	OT (m)	AQR (Ωm)	AQT (m)	COA			(T_j-P_j)	$(T_j-P_j)^2$
49	3	150	12.2	1.09	0.9	0.9	0	0
73	0.5	43	10.2	1.01	1.8	1.2	0.6	0.36
677	3.5	191	9.4	1.17	1.2	1.2	0	0
93	2.5	311	22	1.23	1.7	1.7	0	0
425	0.5	215	15.1	1.01	1.7	1.7	0	0
303	1.7	79	33.3	1.08	1.4	1.4	0	0
32	0.4	52	10.6	1	2.2	2.2	0	0
55	2.4	75	20.5	1.05	1.8	1.8	0	0
115	12.6	50	7.4	1.13	1.7	1.7	0	0
63	0.6	56	16.7	1	1.9	1.9	0	0
98	3.4	103	20.1	1.03	0.6	0.6	0	0
73	4	82	26.1	1.01	2.2	2.2	0	0
54	3.1	138	15	1.24	4.6	4.6	0	0
275	4.9	115	16.5	1.2	2.6	2.6	0	0
102	11.2	85	36.2	1.06	2.6	2.6	0	0
213	15.2	47	19.1	1.33	2.1	2.1	0	0
99	2.1	95	18	1	1.4	1.4	0	0
71	0.8	144	3.4	1.03	1.5	1.5	0	0
567	0.7	265	35.9	1.01	1.4	1.4	0	0
474	6	129	20.2	1.27	2.1	2.1	0	0
51	10.3	145	11.9	1.26	1.5	1.5	0	0
404	8.9	167	12.6	1.28	1.4	1.4	0	0
349	3.5	260	22.7	1.03	1.5	1.5	0	0
76	0.5	82	1.7	1	1.6	1.6	0	0
135	17.1	143	18.8	1.04	1.1	1.1	0	0
734	11.6	347	50.9	1.19	2.1	2.1	0	0
946	30.3	312	48.2	1.37	1.7	1.7	0	0
157	2.4	49	49.1	1.06	1.8	1.8	0	0
262	4	102	15.1	1.18	0.7	0.7	0	0
821	13.4	229	40.2	1.61	3.2	3.2	0	0
1426	31.4	387	43.5	1.13	3.6	3.6	0	0
467	5	123	23.7	1.29	3.1	3.1	0	0
81	0.4	83	1.6	1	2.8	2.8	0	0
131	2.6	13	14.9	1.43	3.1	3.1	0	0
207	0.7	137	3.8	1.62	3.1	3.1	0	0
1528	7.9	228	12.1	1.78	2.7	2.7	0	0
138	2.6	570	19.1	1.11	3.1	3.1	0	0
							Mean square of prediction error = 0.01	

boreholes in the area tap water from the delineated aquifer, this thus suggests that there is justification for predicting groundwater level from the geoelectric parameters obtained from the results of parametric soundings carried in the study area.

The data set was partitioned into training, testing and validation in ratio the 70:15:15, respectively. Apart from the best performance in terms of MSE and R, network with 22 neurons provides simpler architecture needed for better computational efficiency when compared to others. Consequently, the network with 5 inputs, 22 hidden neurons and 1 output neuron was selected.

For training, neural network fits data and R for training is **0.99998** which is high and close to 1. The closeness of the

Table 5 Table for validation data set

Input parameters					Measured GWL output (T_j)	ANN model predicted GWL output (P_j)	Prediction error ($T_j - P_j$)	Square of prediction error $(T_j - P_j)^2$
OR (Ωm)	OT (m)	AQR (Ωm)	AQT (m)	COA				
38	1.7	132	18.1	1.06	1	1.1	−0.1	0.01
169	5.3	92	14.3	1.11	2.2	2.2	0	0
215	5.4	34	18.8	1.92	1.8	1.8	0	0
90	3.1	23	3.9	1.24	1.5	1.5	0	0
608	15	382	41.6	1.11	2.6	2.6	0	0
598	15.5	510	28.1	1.1	2.1	2.1	0	0
112	0.4	204	1.8	1.03	3.2	3.2	0	0
								MSE = 0.0014286

R value to 1 is an indication that both the predicted output and the expected output are well fitted. For testing, neural network fits and *R* for testing is **0.95223**. The model was validated using validation data set which is 15% of the data set and randomly selected. The results of the validation showed that the mean square error (MSE) and the regression coefficient (*R*) for the ANN model were **0.0014286** and **0.98731,** respectively. The results obtained from the validation of the ANN techniques showed that the modeling technique has effectiveness in predicting the groundwater level. This shows that the model is capable of producing effective and reliable prediction results. The model can be applied in other areas of similar geology. Therefore, from the study, the results are satisfactory and demonstrate that neural networks can be a useful prediction tool and it can be concluded that ANN is an effective tool for predicting groundwater level for the purposes of effective planning and management of groundwater resources.

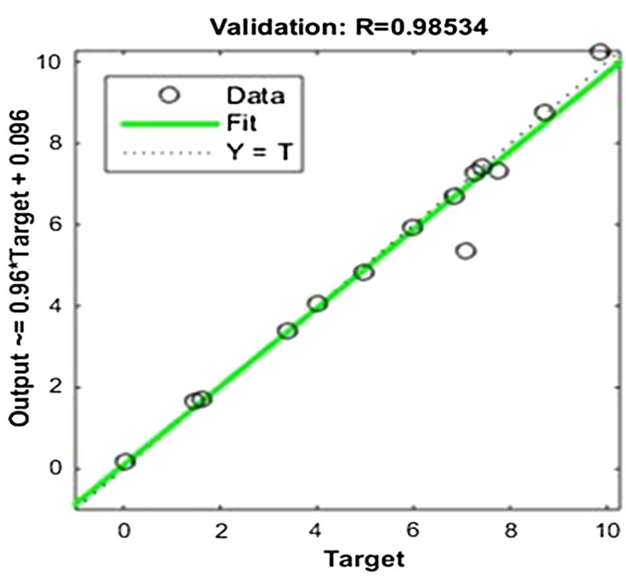

Fig. 6 Regression plot for the validation of the ANN model with 22 hidden layers

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