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(Research Article)

Hybrid Intelligence Model for Reservoir Properties Predictions: A Case Study of the Niger Delta

Tity Eshiet Jackson *, Anietie Ndarake Okon and Christiana Akpan Ukem

Department of Petroleum Engineering, Faculty of Engineering, University of Uyo, Nigeria.

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Abstract

To reliably predict the reservoir's petrophysical properties performance, an accurate model of the reservoir is necessary. Genetic algorithm (GA) and Artificial neural network (ANN) are two well-known techniques for optimizing and learning, as one complements the weakness of the other. This study aims to develop a model using ANN-GA for the accurate prediction of the three fundamental reservoir properties, such as porosity (φ), permeability (K), and water saturation (Sw). The hybrid model was developed using 1304 datasets obtained in the Niger Delta region. These datasets were fed into MATLAB R2015a with an architecture of 10 inputs, 10 neurons, and three outputs using the feed-forward backpropagation method with Levenberg-Marquardt training algorithm. The criteria for evaluating the ANN-GA network performance include mean squared error (MSE), average absolute percentage relative error (AAPRE), coefficient of determination (R^2) and correlation coefficient (R). The developed ANN-GA predicted values, when compared with the field values, showed a significant match. From the results obtained, overall R and MSE values were 0.99039 and 3.5537x10-6 respectively. R values for training, testing, and validation include 0.95765, 0.96674, and 0.95765. Again, the results obtained for the R^2 were φ of 0.9859, K of 0.9816, and Sw of 0.9759. Also, MSE of 1.59952x10-6, 9.71x10-5 and 4.57x10-7 were obtained for water saturation, permeability, and porosity, respectively. The results further indicated AAPRE of 4.57735 for Sw , 1.252225 for K, and 0.04059 for φ. Thus, the developed model provides a better tool for the prediction of the reservoir petrophysical properties.

Keywords: Artificial Intelligence; Genetic Algorithm; Artificial Neural Network; Hybrid Models; Reservoir Petrophysical Properties; Niger Delta

1. Introduction

Petroleum reservoir characterization is a process for quantitatively describing various reservoir properties in spatial variability by using available field data. It plays a crucial role in modern reservoir management in terms of helping to make sound reservoir decisions and also improving the reliability of the reservoir predictions Anifowose and Abdulraheem [1]. It is widely recognized that reservoir characteristics such as: structures, lithofacies heterogeneity, spatial variability of porosity and permeability control the reservoir performance, development strategies and the returns on investment in the reservoir Toba *et al.* [2].

Production of discovered hydrocarbons from a reservoir requires an understanding of the petrophysical and geological properties of the petroleum reservoir Okon *et al.* [3]. These reservoir characteristics include pore and grainsize distributions, reservoir permeability and porosity, facies distribution, depositional environment, and basin description Adizua and Oruade [4]. After hydrocarbon has been discovered in a field, additional studies are carried out to evaluate the reservoir, to understand the reservoir heterogeneity, delineate the extent of the reservoir in three dimensions and

* Corresponding author: Tity Eshiet Jackson

estimate the volume of fluid in the reservoir to know the best development model the reservoir management team will adopt for maximum and efficient reservoir fluid recovery Toba *et al.* [2].

Reservoir characterization is undertaken to determine its capacity to store and transmit fluid. It involves the determination of reservoir properties such as porosity (φ), permeability (k), and fluid saturation (S_w) Ezimadu and Ozebo, [5]. Okon *et al.* [3] reported that porosity (φ), permeability (k), and water saturation (S_w) are three primary properties of petroleum reservoir which define the fluid content capacity of the reservoir pore volume, its ability or potential to transmit fluids during hydrocarbon production and the proportion of the pore space that is occupied by the particular fluid. Again, Worden *et al.* [6] maintained that, the estimation of these reservoir petrophysical properties is vital in the exploration stage of petroleum explorations. Therefore, this makes these reservoir properties key variables for characterizing a reservoir to estimate the volume of hydrocarbons and their flow patterns to enhance the field production Saljooghi and Hezarkhani [7].

Kelkar and Perez [8] opined that, reservoir characterization involves the process of describing the various characteristics (properties) of the reservoir(s) by the use of all available data. Also, Toba *et al.* [2] viewed reservoir characterization as the process of describing various reservoir characteristics such as geologic, petrophysics, geochemical and engineering properties. Hence, it involves using all available data to provide reliable reservoir models for accurate reservoir production and performance prediction, in addition to providing economic and safe decision making to determining the viability of the reservoir (s) under study Jong-Se [9].

Davis [10] submitted that, traditional methods of reservoir characterization using well data provide a limited spatial sampling of reservoir properties. In other words, conventional ways of reservoir characterization do not accurately predict the reservoir petrophysical properties as most of the data obtained have extremities and some of the reservoir parameters used for reservoir characterization are from developed models or correlations Okon *et al.,* [3]. Unfortunately, these correlations cannot handle the discontinuities in the data involved in reservoir characterization Okon *et al*., [3]. This is due to the fact that, petroleum reservoirs are complex and heterogenous with fundamental properties, such as porosity and permeability typically distributed in a non-uniform and non-linear manner Ben-Awuah and Padmanabhan [11]. As a result of these complexities of the reservoirs, it is extremely very difficult to explicitly quantify spatial relationships of variable reservoir properties. However, computer-based intelligence methods like, neural network, genetic algorithm, fuzzy logic can correctly solve this type of complicated problem Ouenes [12]; Nikravesh and Aminzadeh [13]; Nikravesh [14].

Many literatures on the prediction of reservoir petrophysical properties on the application of artificial intelligence have been provided. In the same vein, hybrid models' applications targeted at predicting the same reservoir properties have been provided by few researchers like Nikravesh [14]; Anifowose and Abdulraheem [1]; Khoukhi [15]; Cao *et al.,* [16] and Soumi [17]. Most of the developed ANN and hybrid models available in the literature are multiple-inputs single-output (MISO) that predicts single reservoir petrophysical property: porosity, permeability or water saturation Okon *et al.,* [3]. Also, these models are also not capable of being reproduced as the researchers only provided the models' topology and training (learning) algorithm without the weight and biases of the ANN or hybrid model with limited datasets. Therefore, this study seeks to combine two artificial intelligence techniques (ANN with GA) as a multiple-inputs multiple-outputs (MIMO) model for predicting reservoir petrophysical properties: porosity, permeability, water saturation for reservoir characterization in the Niger Delta region.

The primary aim of this study is to develop hybrid model that will predict the porosity, permeability and water saturation of reservoir properties for reservoir characterization.

The objectives to achieve the primary aim include;

- To develop hybrid model for predicting the porosity, permeability and water saturation of an oil reservoir in the Niger Delta region and,
- To compare the efficiency of the developed hybrid model with existing correlation for estimating the permeability, porosity and water saturation.

1.1. Significance of the Study

The significance of this research is to develop hybrid model that will be used as a quick tool for the prediction of reservoir petrophysical properties for characterization of reservoirs in the Niger Delta.

2. Material and methods

2.1. Data Acquisition and Preparation

Eleven datasets namely depth, bulk volume of water (BVW), caliper logs (CALI), gamma ray log (GR), neutron porosity log (NPHI), total porosity (PHIT), resistivity log (RES), bulk density log (RHOB), surface water testing (SWT), volume of shale (VSH), permeability (K) and water saturation (S_w) were obtained from the Department of Petroleum Resources (DPR).

To make the data suitable for adequate training, testing and validation, the data sets were normalized using Equation 2.1.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \ldots.. \quad (2.1)$$

x_{norm} is the normalized dataset, x is the original dataset, x_{min} is the minimum value of the dataset and x_{max} is the maximum value of the dataset. Equation 2.1 is used to arrange the datasets between the range of 0 and 1 which in turn, makes it suitable for efficient and adequate training.

Hybrid Network Training and Development

Genetic Algorithm (GA) was used together with Artificial Neural Network (ANN) to produce a hybrid model. The choice of GA lies chiefly in its success in literature of optimizing functions effectively and always finding the global minimum. It uses a stochastic approach and thus is rarely stuck in local minima. The hybrid model thus produced, combines the powerful optimization ability of GA with the learning ability of ANN to efficiently solve problems.

To understand how this works, it is important to understand the way ANN works. ANN uses a set of initially randomly generated numbers called weights and biases in its hidden layers to learn about data supplied to it. The learning process is actually done by the neurons in the hidden layers. These neurons are the basic units of a neural network. Each neuron is connected to some or all of the neurons in the next layer. When the inputs are transmitted between neurons, the weights are applied to the inputs along with the biases.

Weights control the signal or strength of the connection between neurons. It is the most important factor in converting an input to impact the output and therefore decides how much influence the input will have on the output. It is similar to slope in linear regression. Biases on the other hand is a constant value, similar to the intercept in linear regression.

The weights and biases in the course of learning are usually fine-tuned or optimized to aid produce the right output. Internally, ANN performs both regression and optimization. This is where hybridization comes in. The algorithm chosen to be used in hybridizing ANN should be able to perform one of the tasks carried out by ANN better than ANN. Fortunately, GA is very good in optimization and can thus assist ANN in that aspect. Thus, the hybridization involves, GA generating the required number of weights and biases, optimizing same and sending it to ANN for its internal regression analysis.

The steps involved can be summarized thus:

- The network is chosen (feedforward backpropagation).
- GA is requested to send in the initial weights and biases for training to start.
- ANN receives the weights and biases, performs internal calculation using the training function. The result is sent to GA, who uses an error function supplied to it to assess the performance of the network.
- GA optimizes the weights and biases, and sends the newly optimized weights and biases to ANN who performs its internal calculation and sends the feedback to GA. Thus, a loop is created from step iii to iv. This loop runs until a stopping criterion supplied to GA is met.

2.2. GA Settings

The genetic algorithm was developed using the parameters as follows: The population size is the number of individuals in the population; large number of individuals increases the population diversity, but also increases the computation time effort. In this research, the population size was 300. The maximum number of generations was 300 because the larger the generation the more accurate the result will be and it was observed that, excessive training of the network resulted in a loss threshold. The maximum stall generation was set at 20, it enabled the GA to create a space limit to find a better solution. Also, all other options were set to take up the default values the GA gives to the network. They are represented by [ ] and shown in Table 1.

2.3. Statistical Error Analysis

Statistical error analysis was performed to evaluate the performance and accuracy of the developed model. The statistical parameters used for the evaluation are: average percent relative error (APRE), average absolute percent relative error (AAPRE), mean squared error (MSE) and coefficient of determination (R^2).

2.4. Average Percent Relative Error

It is the measure of the relative deviation from experimental data, defined by;

$$E_r = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\frac{RP_f - RP_{pred}}{RP_f}\right) * 100\right] \tag{2.2}$$

2.5. Average Absolute Percent Relative Error

It is the measure of the relative deviation from experimental data, defined by;

$$E_A = \frac{1}{n}\sum_{i=1}^{n}\left|\left(\frac{RP_f - RP_{pred}}{RP_f}\right) * 100\right| \tag{2.3}$$

2.6. Mean Square Error

The mean squared error (MSE) shows how close a regression line is to a set of points. It does this by taking the distances from the points to the regression line. (These distances are the error) and squaring them.

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(RP_f - RP_{pred})^2 \tag{2.4}$$

2.7. The Coefficient of Determination

It represents the degree of success in reducing the standard deviation by regression analysis defined by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(RP_f - RP_{pred})^2}{\sum_{i=1}^{n}\left(RP_f - RP_{\overline{pred}}\right)^2} \tag{2.5}$$

where RPf is the value of the experimental reservoir properties (porosity, permeability and water saturation) fed to the model, RP_{pred} is the models' predicted reservoir properties, and $RP_{\overline{pred}}$ is the average ANN predicted reservoir properties.

3. Results and Discussion

A feedforward neural network with 10 inputs, 1 hidden layer with 10 neurons and 3 outputs was formed. Thus, the structure of the developed model is [10 10 3]. Another layer called an "output" layer is usually added internally by ANN. The topology of the said network is shown in Figure 1. The Levenberg Marquardt function was used as the training function for the network and the sigmoid function as the transfer function in the output layer. 1304 data points were used for the training.

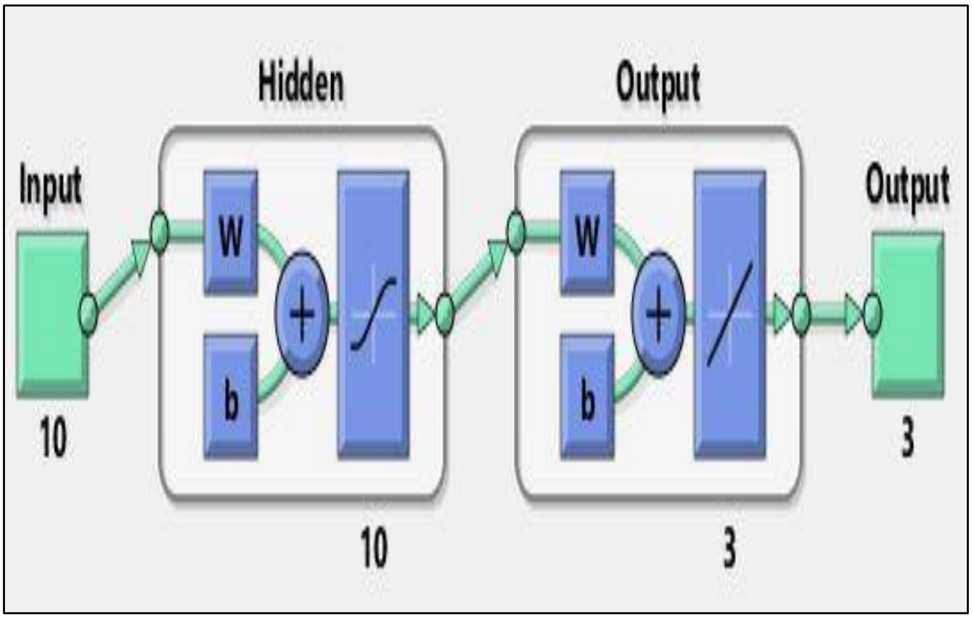

Figure 1 Topology of neural network

The ANN_GA model with the properties described above was used for the hybridized training. The simulations were run using MATLAB® 2015a installed on a laptop running Intel® core i5-3320M with 4Gb RAM and 2.6Ghz processing speed.

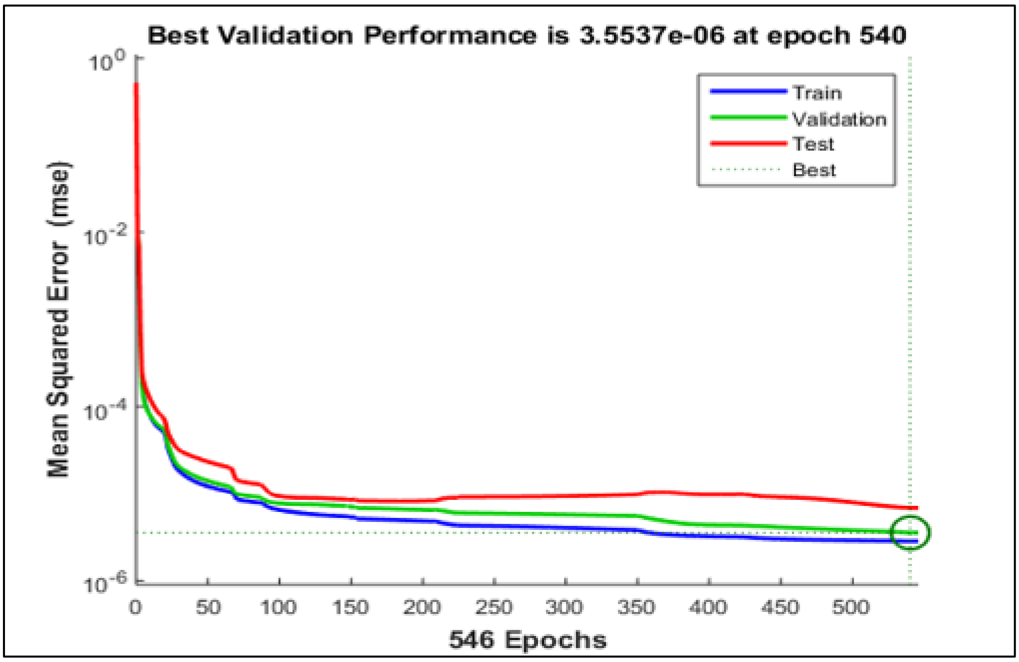

Figure 2 Hybrid Network Training Performance

Figure 2 shows the trend of the mean squared error (MSE) during training, testing and validation, as the number of epoch increases. This eventually resulted in the optimal performance during validation at 540th epochs, having MSE value of 3.5537e-6 approximately. The behaviour of the ANN_GA training performance shows that the network learns better, as the number of epoch increases. The single-layer configuration (ANN_GA [10-10-3]).

3.1. Analysis of Result

Figures 3 and 4 shows the regression plot of the ANN-GA. From the figures it can be seen that ANN-GA has a correlation coefficient of 0.99039. This value is quite high and show good performance as it is close to one (1).

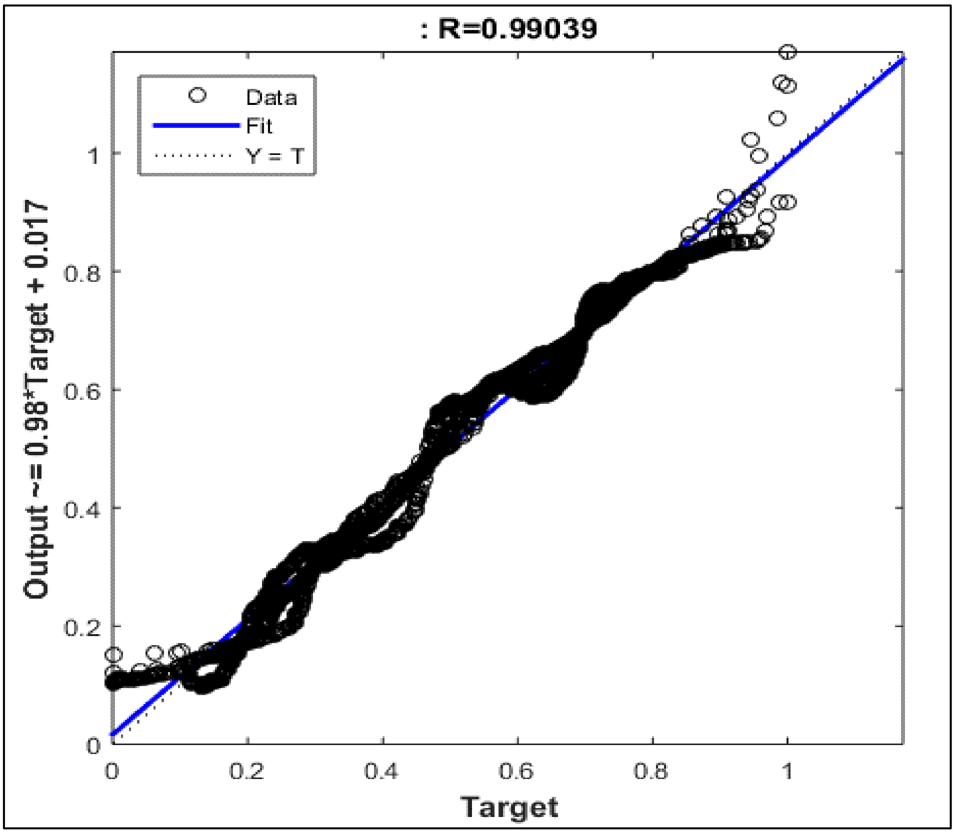

Figure 3 Overall Regression Plot for ANN-GA

Figure 3 shows the overall ANN_GA regression plot obtained after the successful running of the network.

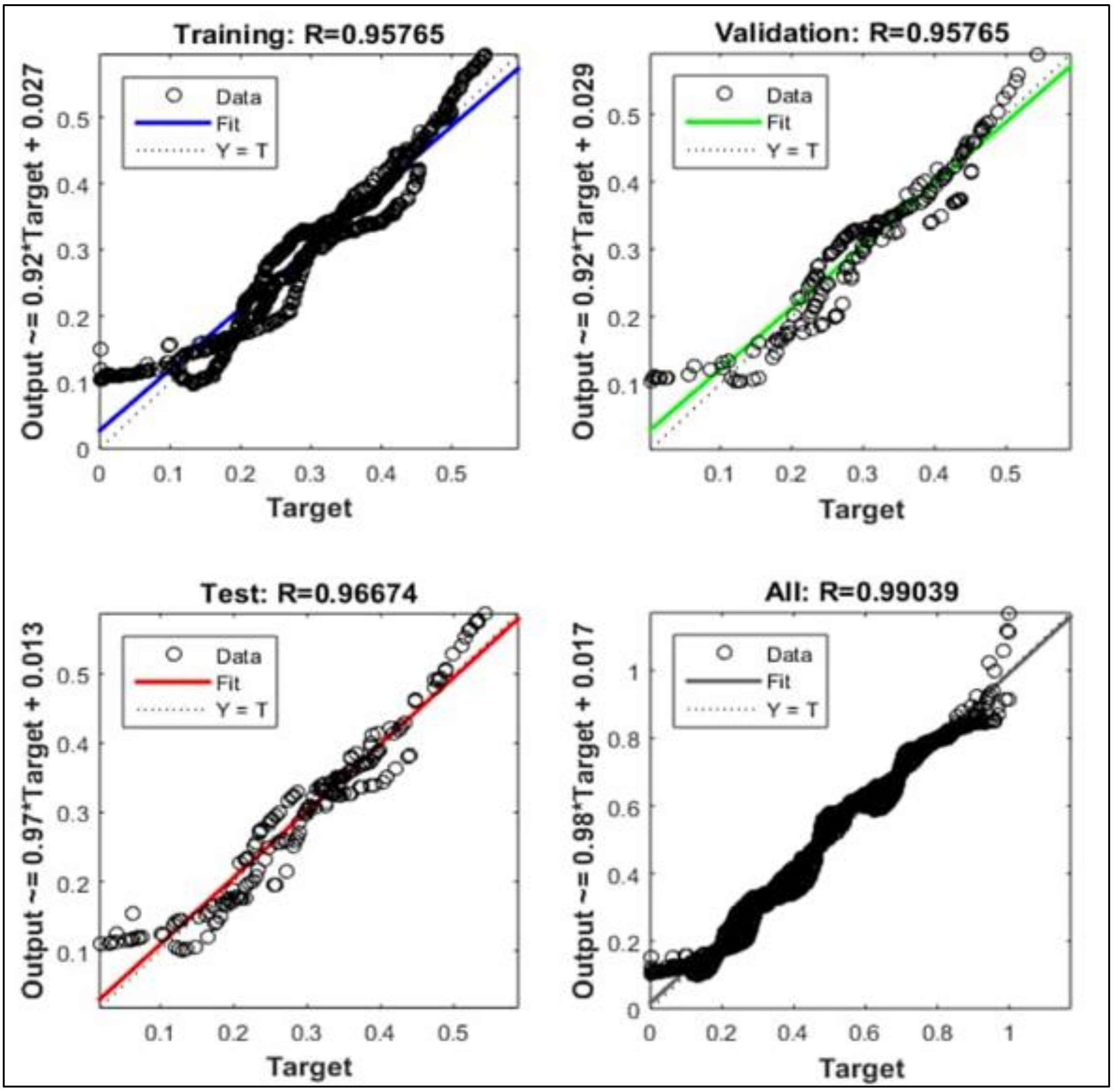

Figure 4 Regression plot for ANN_GA

Figure 4 shows the regression plot of the ANN_GA model for the training, testing and validation. It shows how close the predicted outputs are to the field datasets.

Table 1 Parameters Settings for ANN_GA Optimization

Parameters	Settings Used
EliteCount	[ ]
FitnessLimit	1.0000e-10
FitnessScalingFcn	[ ]
MaxStallTime	20
NonlinearConstraintAlgorithm	[ ]
SelectionFcn	[ ]
ConstraintTolerance	1.0000e-10
CreationFcn	[ ]
CrossoverFcn	[ ]
CrossoverFraction	[ ]
Display	'iter'
FunctionTolerance	1.0000e-10
MaxGenerations	300
MaxStallGenerations	20
Performance Gradient	[ ]
Fitness Value	[ ]
MaxTime	[ ]
MutationFcn	[ ]
PopulationSize	300
PopulationInitialRange	0, 1
UseParallel	0
UseVectorized	0

3.2. Cross Plots

To further assess the performance of the network, cross plots were generated for the three outputs – porosity, water saturation and permeability. They are shown in Figures 5 through 7.

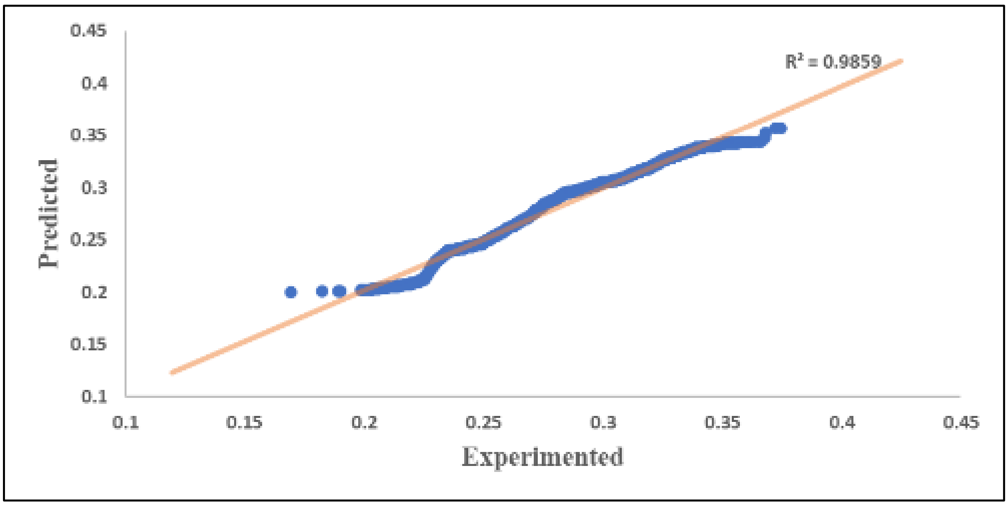

Figure 5 Porosity Cross Plot

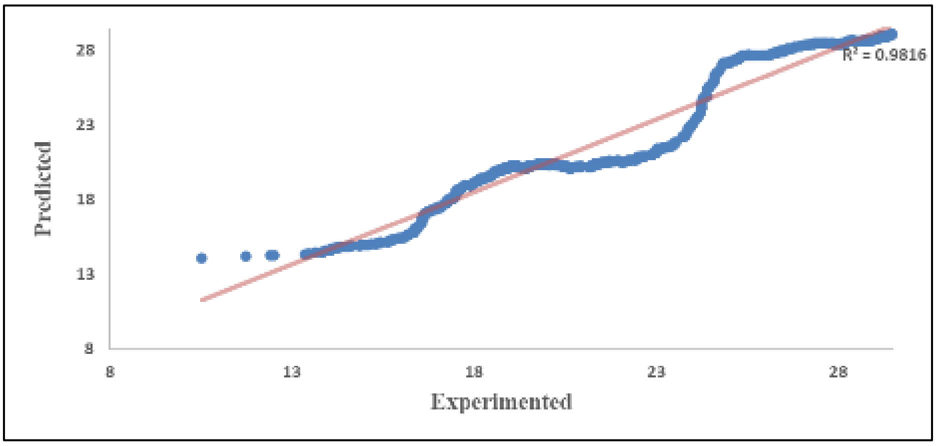

Figure 6 Permeability Cross Plot

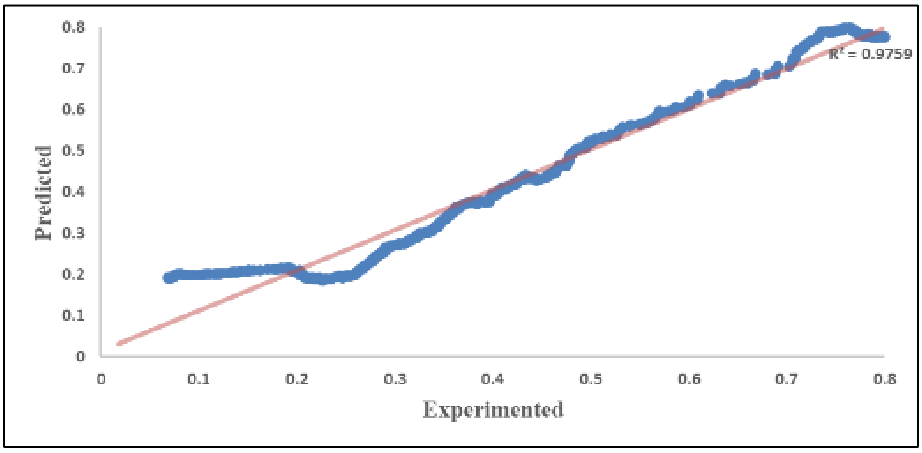

Figure 7 Water Saturation Cross Plot

3.3. Weight and Biases

Table 2 Weight and Biases from Neurons to Hidden Layers

WEIGHTS AND BIASES FOR ANN-GA														
1W1										1W2			B1	B2
-2.3929	1.1398	0.7331	0.7331	-0.7992	0.8299	0.1549	0.1199	0.6218	0.8309	0.1563	0.3353	0.2229	0.8754	0.3250
0.8996	-0.4327	0.6149	0.6149	0.4358	1.2527	0.8924	0.5109	0.1505	1.1217	0.3313	0.1834	-0.032	3.0059	0.9285
0.7187	0.3841	0.5492	0.5492	-1.2724	-0.4952	3.1592	1.3271	-0.5864	-1.6534	0.4152	0.1325	0.1575	-1.4949	-0.3305
0.1313	-0.9175	0.7424	0.7424	1.4500	-0.2807	0.4479	-1.0046	0.7279	2.1879	0.1816	0.4025	-0.1072	0.5960	
-0.7023	0.3053	-0.3376	-0.3376	-0.3584	2.2394	1.2378	0.5137	0.1048	0.9689	0.2579	0.3687	0.1789	1.8242	
0.9656	0.1898	-1.2716	-1.2716	0.0239	1.1636	0.4677	-0.3797	0.1321	0.1631	-1.9279	-1.2381	0.2502	0.0776	
0.6195	0.5152	0.4649	0.4649	0.1995	0.3413	0.8732	0.2153	-0.3586	-0.0375	0.7327	0.5565	0.2951	1.0809	
0.2594	0.6240	0.6754	0.6754	0.0484	0.4185	0.5825	0.6962	0.9785	1.0016	0.7823	0.2705	0.3691	1.7189	
0.4050	-0.2994	-1.6052	-1.6052	0.8123	0.9742	-0.2464	-1.0067	0.2816	0.7173	-0.0643	-0.9298	0.4635	1.5364	
-0.1108	2.0018	-0.9444	-0.9444	-0.2782	1.3325	0.6764	0.6275	0.4322	0.6543	0.1569	-0.1399	-0.4277	0.6857	

$$[phit, sw, k] = f_{output}\left\{\sum_{k=3}^{3}\left(f_{input}\sum_{j=1}^{10}\sum_{i=1}^{10}\left(\left(Dw_i^j + BVWw_i^j + CALIw_i^i + DTw_i^i + GRw_i^i + NPHIw_i^i + RESw_i^i + RHOBw_1^i + VSHw_i^i + SWTw_i^i\right) + b_1^1\right)\right) * Lw_1^2 + b_k\right\} \tag{3.1}$$

Equation 3.1 represents the model developed by ANN_GA to predict the porosity, permeability and water saturation. Where, D = depth, BVW= Bulk volume of water, CALI = caliper log, DT= Sonic transit time, GR = gamma ray, NPHI = neutron porosity, RES = resistivity log, RHOB = bulk density, VSH = volume of shale, SWT = surface well testing, bi = bias attached to the input, b_k = bias attached to the output, f_{output} = activation function for output (sigmoid), f_{input} = activation function for input (TANSIG). The equation shows the trained ANN_GA model correlating the ten (10) input parameters and the porosity, permeability and water saturation as the final output in MATLAB. Here, 'tansig' is the MATLAB activation functions which calculate the layer's output from its network input. Tansig is a hyperbolic tangent sigmoid transfer function and is mathematically equivalent to 'tanh'. Tansig is faster than tanh in MATLAB simulations, thus it is used in neural networks. The tansig relation is defined by Equation 3.2.

$$Tansig = \frac{2}{[1 + Exp(-2network) - 1]} \tag{3.2}$$

Therefore, to predict the porosity, water saturation and permeability, Equation 3.2 and the values in Table 2 were used.

4. Conclusion

ANN_GA model was used to predict the three fundamental reservoir properties. These properties include, porosity (φ), permeability (K) and water saturation (S_w). From the results obtained, the following conclusions can be drawn: The developed models' predicted porosity, permeability and water saturation performed better than existing works with the ANN_GA model having an overall mean squared error of 3.5537e-06, overall correlation coefficient (R) of 0.99039 and a coefficient of determination (R^2) of 0.9859, 0.9816 and 0.9759 for porosity, permeability and water saturation respectively.

Hence, the developed model can be used to predict the three fundamental reservoir properties such as, porosity (φ), permeability (K) and water saturation (S_w) for reservoir characterization. This accurate prediction of the reservoir petrophysical properties is beneficial to the oil and gas sector and the society at large as it ensures efficient extraction of resources, aids economic growth, protects the environment and ensures proper resource management for the society. Therefore, it is recommended that companies invest resources in creating predictive systems using hybrid intelligence models.

Compliance with ethical standards

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Disclosure of conflict of interest

We declare that, although we were faced with a few financial challenges during the course of the research. However, these challenges did not influence the results or conclusion drawn from the research in any way.

Statement of ethical approval

This is to declare that the present research work does not contain any studies performed on animals/humans subjects by any of the authors

Statement of informed consent

There were no participants or human case study to the research article aside all authors of this research work and support from friends and family duly noted under the acknowledgement section.

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Author's short biography

Authors Name: Tity Eshiet Jackson Tity Eshiet Jackson is a passionate Petroleum Engineering graduate who enjoys leveraging technological innovations in solving global problems in the oil and gas sector. Her immense fondness for artificial intelligence and data analytics propels her to seek ways in which energy operations can be safer and more efficient. Her research area focuses on reservoir petrophysical properties and simulations hence, she is committed to using her skills as a data analyst to make informed decisions in the energy sector. Also, her knowledge of health and safety practices from Envirofly (Flexy learn international) and her strong background in petroleum engineering gives her an advantage to drive sustainable and technological change in the energy industry. Her career goal is to advance her studies at a master's level with plans to progress into a Ph.D. program in reservoir engineering. She is therefore open to opportunities for industry exposure that would ultimately help her contribute back to the society and drive sustainable innovations in the energy sector through the experiences and knowledge gained.	
Authors Name: Christiana Akpan Ukem Christiana Akpan Ukem, is a recent Petroleum Engineering graduate with a Second-Class Upper Division. In addition, she obtained a distinction in Data Processing and Information from the IMF-ICT Academy, Uyo, Nigeria. She possesses strong technical expertise in petroleum engineering laboratory practices, with hands-on experience in analyzing drilling mud properties. She has nearly one year of professional experience as a Laboratory Assistant, where she gained valuable exposure to laboratory operations and analytical techniques. Beyond engineering, she has also built over three years of teaching experience at Air Force Comprehensive Secondary School, where she taught Chemistry and supported laboratory experiments. This role enhanced her skills in communication, collaboration, and leadership while deepening her ability to simplify complex concepts for learners. She is passionate about advancing her knowledge through industrial exposure and research. Her career goals include pursuing a master's degree and ultimately a Ph.D. in petroleum engineering, while contributing to innovation and sustainable practices in the energy sector.