Volumetric Approach Based DOE and ANN Models for Estimating Reservoirs Oil in Place

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Abstract— The volumetric approach of estimating reservoir oil in place (OIP) at the appraisal stage is characterized with uncertainty; as the available reservoir data used for this evaluation are average values. To assess the uncertainty associated with the volumetric method, reservoir data, namely, initial water saturation (S_{wi}), initial formation volume factor (B_{oi}), porosity (φ), oil column (h) and reservoir area (A) from three fields: Philus, Otu and Unnamed field in the Niger Delta were obtained. Monte Carlo simulation was performed with these fields' data to establish their proved, probable and possible reserves (3PR) values. The results obtained showed that Philus field had 0.199, 0.235 and 0.266 billion STB and the Otu field had 0.019, 0.024 and 0.029 billion STB while the Unnamed was 0.728, 0.870 and 1.004 billion STB. Volumetric estimation of these fields OIP was 0.21, 0.02 and 0.78 billion STB for Philus, Otu and Unnamed field respectively. These estimations indicated that the fields' estimated OIP were less than their proved reserves but more than their probable and possible reserves. Also, the uncertainty associated with the estimated OIP from the volumetric approach was between 18% to 20%. Furthermore, alternative models based on the design of experiment (DOE) and artificial neural network (ANN) were developed for estimating/predicting the fields OIP. The DOE model estimation was 0.2105, 0.0210 and 0.7489 billion STB for Philus, Otu and Unnamed field, respectively, while ANN model prediction was 0.2556, 0.028 and 0.6303 billion STB. Comparing the developed models' estimations with volumetric equation depict that the DOE model had a coefficient of determination (R^2) of 0.9971, mean square error (MSE) of 0.0003, root mean square error (RMSE) of 0.0172 and mean absolute error (MAE) of 0.0106, while ANN model had R^2 of 0.9241, MSE of 0.0079, RMSE of 0.0891 and MAE of 0.0640. Besides, the developed ANN model average contribution factor of the input variables was 18.82% for S_{wi} , 30.51% for B_{oi} , 19.48% for φ , 14.78% for h and 16.41% for A. Hence, the developed DOE and ANN models can be used as an alternative tool to estimate reservoir OIP in the Niger Delta with a superior certainty.

Keywords: Volumetric approach, Design of experiment, Artificial neural network, Monte Carlo simulation, Oil in place, Niger Delta.

1 Introduction

In the petroleum industry, to make sound production investments, decision-makers require accurate estimates of the reservoir reserves [1]. These estimates are to establish the volume of oil in the reservoir(s), which is referred to "oil in place" in petroleum engineering. Oil in place (OIP) is the total volume of oil in a reservoir, which when estimated, helps in decisions making such as production schedule and updating the investors about future gains or losses [2]. This must be properly estimated to give the explorers an idea of the ultimate potential of the field. Depending on the stage of appraisal of the reservoir, various methods can be used to estimate the reservoir oil in place, namely, volumetric method, material balance method, decline curve analysis and mathematical simulation [3]. For instance, when a newly discovered reservoir which lacks much data is evaluated, volumetric method is used to estimate the oil in place. After production has begun, the material balance method is used to estimate the reservoir oil in place by analyzing the pressure changing parameters, namely, fluid formation volume factors, solution gas-oil ratio, fluid saturation, etc. over time, together with the production history from that reservoir.

In earnest, the volumetric method of oil in place estimation is mostly used in appraising wells with little or no prior data from the reservoir. As a result of limited data at the developmental stage of the reservoir, average reservoir parameters are used for the volumetric estimation [4]. Over the years, the industry has been faced with the challenge of uncertainty in the estimation of oil in place using the volumetric approach. This is because the average reservoir parameters used for the estimation consider reservoir as uniform and homogenous media. The sensitivity of this challenge has made many authors to quantify the uncertainty associated with reservoir oil in place estimation using various approaches. According to Murtha [5], to assess the uncertainty associated with the paucity of available datasets on the volumetric estimates of reservoir oil in place, statistical method such as Monte Carlo simulation is often used.

The Monte Carlo simulation also known as probability simulation is a process of running a model numerous times with a random selection from the input distributions for each variable [6]. Murtha [7] defined it as a technique used to generate a set of predicted data, obtained from random sampling for a probability distribution as it seeks to duplicate reality as closely as possible within practical limitations. Further, Fylling [8] explained that the simulation applies random number generators to draw input values from some user-specified distributions, and one value of output is calculated from each set of drawn values. By repeating this process a sufficient number of times, the uncertainty of the output can be estimated from the generated output

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ISSN 2229-5518

distribution. In other words, Monte Carlo simulations are used to model the probability of different outcomes in a process that cannot easily be predicted due to the intervention of random variables [9]. Its application helps to understand the impact of risk and uncertainty in prediction and forecasting models.

In 2005, Wadsley [10] developed a Monte Carlo based approach called the Markov Chain Monte Carlo simulation for estimating reservoir reserves. The method was able to combine independent estimates of the reservoir initial oil in place (OIIP) obtained from decline curve analysis, material balance and volumetric methods to a robust and unbiased estimate of reservoir oil in place. In another study, Masoudi *et al*. [11] presented deterministic and probabilistic approach for estimating reservoir oil in place of a multilayered gas reservoir in the Persian Gulf. These methods included the probable effect of the uncertainties in the field hydrocarbon volume, and in the producing layer's hydrocarbon volume. Again, Efeoghene [12] assessed the uncertainty in reservoir oil in place by building a grid-based model of the reservoir. He evaluated the petrophysical properties that affect the volumes of fluids in place by assigning various probability distribution functions to some of the reservoir parameters. Then, he generated one hundred realizations of the reservoir oil in place using Monte Carlo simulation to determine the possible, probable and proved reserves at P10, P50 and P90 values, respectively. The values obtained showed a general decrease in the reservoir oil in place for each zone with an increase in the depth. However, the limitation of the study was that the grid cell-based method did not define the reservoir attributes on a grid block scale and various objects with different shapes and sizes could not be modelled and simulated. In this study, Monte Carlo simulation will be used to establish the proved, possible and probable reserves (3PR) of the reservoirs as well as assess the uncertainty associated with the volumetric approach of estimating reservoir oil in place in the Niger Delta fields. Further, alternative models based on design of experiment (DOE) and artificial neural network (ANN) for estimating reservoir oil in place will be developed.

1.1 The Volumetric Approach of Estimating Reservoir Oil in Place

The volumetric method of reservoir oil in place estimation involves the use of static reservoir properties such as the area of accumulation, pay thickness, porosity and initial fluids saturation [11]. The volumetric equation for estimating oil in place is expressed in Equation 1. It estimates the oil in place from the physical properties of the reservoir using either the deterministic or probabilistic approach. The deterministic evaluation uses static and dynamic models to quantify the reservoir oil in place [13]. Here, the outcome of the reservoir oil in place is derived for each deterministic scenario, and a single best estimate of the reservoir oil in place is made based on known geological, engineering and economic data. In probabilistic evaluation, a distribution representing the full range of probable values is defined for each input parameter. This involves the generation of probability distribution functions (PDFs) for each volumetric parameters, that is, oil formation volume factor (B_{oi}), porosity (φ), oil column (h), initial water saturation (S_{wi}) and reservoir area (A). Then, the parameters PDFs are combined statistically with the reservoir oil in place PDF constructed to define the uncertainty in a particular parameter [14]. Since deterministic evaluation cannot handle uncertainties in input (reservoir) parameters, where a high uncertainty is expected, the applicability of the probabilistic approach is more viable compared to the deterministic method [15]. Hence, the probabilistic approach is most often applied to the volumetric reservoir oil in place estimations in the early phase of exploitation and field development.

$$OIP = \frac{7758\varphi Ah\left(1-S_{wi}\right)}{B_{oi}} \tag{1}$$

where;

A = area of reservoir, acres
h = average reservoir thickness, ft
φ = porosity, fraction
S_{wi} = initial water saturation, and
B_{oi} = initial oil formation volume factor, bbl/stb.

1.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational systems designed to simulate the operating principles of the biological nervous system using numbers of simple interconnected neurons [16]. Their diverse applications are as a result of the networks' ability to mimic the human brain. They are based on simulated neurons modelled as nodes arranged in layers and linked together in a variety of ways to form networks. According to Schaid *et al.* [17], each node receives impulses from all the nodes in the layer before it and sends an impulse to each node in the layer following it. The strength of connections (linkage value) among pairs of nodes in adjacent layers is called weights, and iteratively estimating these weights is called training a network [17]. Each input to a neuron is multiplied by the linkage weight, and all inputs are summed together to give the net input. Each neuron has an

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ISSN 2229-5518

activation function, which affects the net input. The output of the activation function is then transferred to the other neurons. The general relationship between the input and output in an ANN model is given by Equation 2 [18].

$$y_k = f_o\left[\sum_j w_{kj}\cdot f_h\left(\sum w_{ji}x_i + b_j\right) + b_k\right] \qquad (2)$$

where x_i represents an input vector; w_{ji} and w_{kj} are the connecting weights from the *i*th neuron in the input layer to the *j*th neuron in the hidden layer and *j*th neuron in the hidden layer to the *k*th neuron in the output layer; b_j and b_k denote the biases of *j*th hidden neuron and the *k*th output neuron; and f_h and f_o are the activation functions for the hidden and output neuron, respectively.

These networks can learn, memorize and create relationships amongst data sets. The strategy by which the optimized weight values are earned is called learning. In the learning process, it tries to teach the network the way to turn out the output once the corresponding input is given. Once learning is complete, the trained neural network, with the updated best weights, ought to be ready to produce the output at intervals, with the desired accuracy equivalent to the associate input pattern. Learning strategies for ANNs include supervised learning, unsupervised learning and reinforced learning. ANNs have a variety of applications across various industries and have been effective in performing advanced functions such as pattern recognition, natural language processing and speech understanding. The pith of Artificial Intelligence (AI) is its ability to store a large amount of information and process it at very high speed.

1.3 Design of Experiments

Experiments are sequence of tests carried out to evaluate response, by making purposeful changes to the input variables to identify the reasons for changes in the output variable or response [19]. In 2003, Zhang [1] defined design of experiments (DOEs) as an uncertainty analysis method which is used to obtain maximum information at minimum experimental cost, by varying all the uncertain parameters simultaneously. In other words, it is a strategy in which the input variables (reservoir parameters in this case) are varied simultaneously, in a series of experimental runs according to a predefined design matrix to obtain experimental response STOOIP [19]. Design of experiment is used to determine which parameters have the greatest uncertainties, so as to evaluate their impacts on production forecast to expedite decision making in reservoir development planning [20]. It ensures that most or all the possibilities of alternative relationships between the variables are identified, by searching for relationships rather than merely describing the results. Thus, a design is selected to obtain the experimental response without understanding the experiment behaviour, and then an equation is fitted as a surrogate model for the response under study. For effective implementation of the design of the experiment, the matrix for selecting the design runs and determining the best design model must be followed. This matrix is determined by the number of factors and levels of the experiment.

2 RESEARCH METHODOLOGY

2.1 Data Acquisition and Monte Carlo Simulation

The basic data for estimating reservoir oil in place (OIP) of Niger Delta fields using volumetric approach were obtained from the works of Nwankwo *et al*. [21], Obiekezie and Bassey [22] and Sunmonu *et al*. [23]. These parameters are presented in Table 1. Generally, the volumetric approach of reservoir oil in place estimation is an average data method which its estimation is associated with uncertainty [24]. To evaluate the uncertainty that associates with these fields' reservoir oil in place estimation, Monte Carlo simulation (i.e., probabilistic or stochastic method) was performed with the average reservoir parameters in Table 1. Five thousand (5000) normal distribution random numbers were generated using Microsoft Excel function. The minimum and maximum values of each reservoir parameters were established based on the expanded Equations 3 and 4. This evaluation resulted in a total of ten thousand (10,000) samples data for each reservoir parameters of the three (3) fields. To ensure the reservoir parameters used for the simulation were in the range of realistic values for a typical Niger Delta field, ranges were set for porosity (φ), initial water saturation (S_{wi}) and initial oil formation volume factor (B_{oi}). These were between 0.15 – 0.43 for φ, 0.15 – 0.50 for S_{wi}, and 1.0 – 2.0 for B_{oi}. Thus, the generated 10,000 sample data were sorted based on the adopted criteria and 1708 sample data of each reservoir parameters met the mentioned yardsticks. Hence, the reservoir oil in place of the 3 fields was estimated to establish their 3PR-values: the proved, possible and probable reserves using the probabilistic (stochastic) method.

$$Value_{\min} = Value - Value \times \left(RAND(\ )\right) \qquad (3)$$

$$Value_{\max} = Value + Value \times \left(RAND(\ )\right) \qquad (4)$$

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ISSN 2229-5518

Table 1: Reservoir parameters obtained from Niger Delta fields

Field Name (Reservoir)	Source	S_{wi}	B_{oi} (bbl/Stb)	φ	h (ft)	A (acres)	OOIP (bbl) (Billion)
Philus Prospect (Sand E)	Sunmonu *et al.* [23]	0.40	1.2	0.24	72.31	3154.26	0.21
Unnamed (HD 2000)	Nwankwo *et al.* [21]	0.35	1.05	0.31	400	1307.38	0.78
Otu (D10)	Obiekezie and Bassey [22]	0.25	1.45	0.34	36.25	432.97	0.02

2.2 Volumetric Approach Based Models Development

2.2.1Design of Experiment (DOE) Based Model

A full factorial design of experiment was performed using Minitab 17 software. The design was five (5) factors, namely, S_{wi}, B_{oi}, φ, h and A, with two (2) levels (i.e., high and low) for each factor, hence, 2^5 experiments which amount to 32 outcomes. The data used for the DOE-based model development were as established from the Monte Carlo simulation (Table 2). Based on the designed experiment matrixes on the reservoir parameters, the corresponding reservoir oil in place was evaluated and imported into the Minitab software to establish the DOE-based model for the fields' oil in place. Applying a multivariate optimization technique, the established DOE-based model performance was optimized using Microsoft Excel Solver. The validity of developed DOE-based model with volumetric equation estimations was established using statistical indicator – coefficient of determination (R^2) and cross plot.

Table 2: Design of Experiment low and high level values

Field	Levels	S_{wi}	B_{oi} (Bbl/STB)	φ	h (ft)	A (Acres)
Philus	Low	0.38	1.15	0.23	69.14	3015.99
	High	0.48	1.45	0.29	87.16	3801.83
Otu	Low	0.24	1.39	0.33	34.79	415.59
	High	0.30	1.75	0.41	43.79	523.05
Unnamed	Low	0.34	1.01	0.29	382.95	1251.65
	High	0.42	1.27	0.37	482.48	1576.95

2.2.2 Artificial Neural Network (ANN) Based Model

The ANN model for estimating reservoir oil in place was developed using neural network fitting (nftool) in MATLAB 2015a software based on the data obtained from the Monte Carlo simulation, that is, 5124 datasets for each input parameters. Statistical descriptions of these data are presented in Table 3. Based on the volumetric approach, the ANN network input variables were initial water saturation (S_{wi}), oil formation volume factor (B_{oi}), porosity (φ), oil column (h), and reservoir area (A) data. The input and targeted data were normalized using maximum and minimum data points as expressed in Equation 5;

$$Nor(x_i) = \frac{x_i - Min(x)}{Max(x) - Min(x)} \quad (5)$$

where $Nor(x_i)$ is the normalized parameter (input or output), $Min(x)$ and $Max(x)$ denote the minimum and maximum values of the actual parameters and x_i is the actual parameter (input or output). These normalized datasets in the MATLAB software were partitioned into three (3) parts, namely, the training set (70%), test set (15%) and validation set (15%). The network training was supervised learning based on the Levenberg-Marquardt algorithm since the reservoir oil in place was provided as the target. After several trials of different network topologies (i.e., architectures), the optimum network performance was obtained with five (5) input neurons, ten (10) neurons at the hidden layer and one (1) output neuron, thus, 5-10-1 network architecture (Fig. 1). The basic details of the ANN model are presented in Table 4.

Table 3: Statistical description of the ANN input data

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ISSN 2229-5518

Statistical tool	S_{wi}	B_{oi}	φ	h	A	OIP
Mean	0.3611	1.3373	0.3214	183.6729	1767.7485	376069137.7
Maximum	0.4999	1.8127	0.4250	499.9967	3942.7988	1050278572
Minimum	0.2292	0.9648	0.2200	33.2297	396.8948	18491121.36
Standard deviation	0.0751	0.2149	0.0539	178.7598	1244.0248	364775020.7
Coefficient of variation (%)	20.7990	16.0666	16.7590	97.3250	70.3734	96.9967977

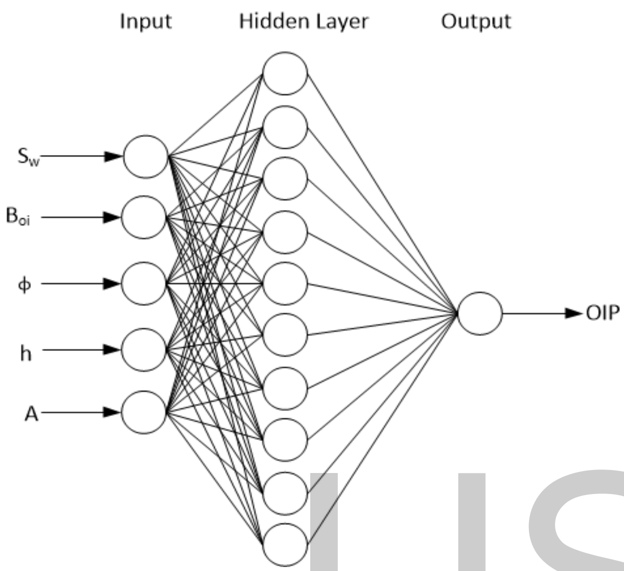

Fig. 1, The artificial neural network architecture

Table 4: Basic parameters of the ANN model

Parameters	Values
Training dataset	3588 (70% of datasets)
Testing dataset	768 (15% of datasets)
Validation dataset	768 (15% of datasets)
Number of input neurons	5 (S_{wi}, B_{oi}, φ, h, & A)
Number of hidden layer	1
Number of neurons in hidden layer	10
Number of output neurons	1
Input activation function	Tansig
Output activation function	Purelin
Learning algorithm	Levenberg-Marquardt
Mean square error (MSE)	1.5327e-09
Number of epochs	498

3 RESULTS AND DISCUSSION

3.1 Reserves Estimation and Associated Uncertainty

Figs. 2 through 4 present the fields' reserves curves obtained from the Monte Carlo simulation approach. From these curves, the 3PR (i.e., proved, probable and possible reserves) of the fields were obtained at P90, P50 and P10 values, respectively. These results are presented in Table 5.

From the Table, Philus field's 3PR values was 199 MMSTB (0.199 billion STB), 235 MMSTB (0.235 billion STB) and 266 MMSTB (0.266 billion STB) for proved, probable and possible reserves. Also, the Otu and Unnamed fields had 0.019 and 0.728 billion STB for proved reserves, 0.024 and 0.871 billion STB for probable reserves, and 0.029 and 1.005 billion STB for possible reserves. On the other hand, estimation of the fields' oil in place (OIP) based on volumetric approach (Equation 1) resulted in 0.21 billion STB, 0.02 billion STB and 0.78 billion STB for Philus, Otu and Unnamed field, respectively. These deterministic volumetric approach results, when compared with the probabilistic method results, showed that the estimated reservoir oil in place (OIP) for the various fields are less than the proved reserves of the fields. However, it is observed that the estimated OIP of the fields are more than the fields' probable and possible reserves. Therefore, it is pertinent to classify and quantify the uncertainty associated with the volumetric approach of estimating reservoir OIP. Based on Figs. 2 through 4, the fields' estimated OIP had probability (certainty) of 82.06% for Philus field, 80.63% for Otu field, and 81.04% for Unnamed field (Table 6). As observed from the associated certainty of the estimated fields' OIP, it shows that the volumetric approach estimation of the fields' OIP is within 80% - 82%. This observation simply translates to there is 18% - 20% uncertainty associated with the volumetric approach for estimating reservoir oil in place (OIP).

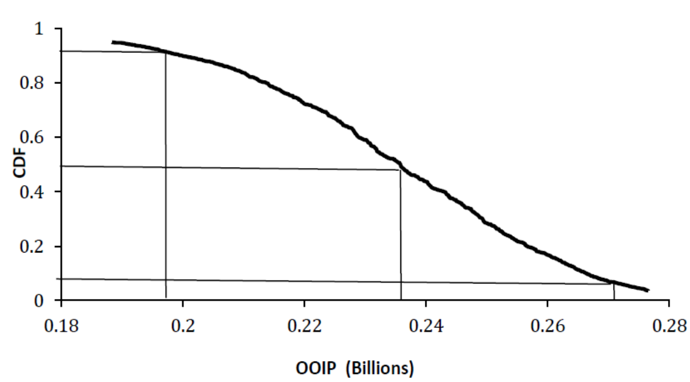

Fig. 2, Reserves curve for Philus field

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ISSN 2229-5518

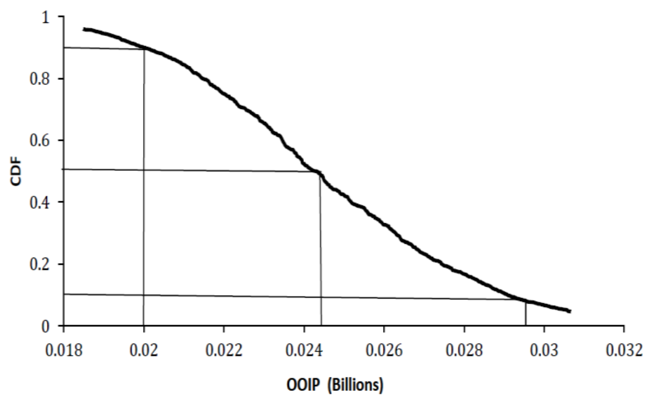

Fig. 3, Reserves curve for Otu field

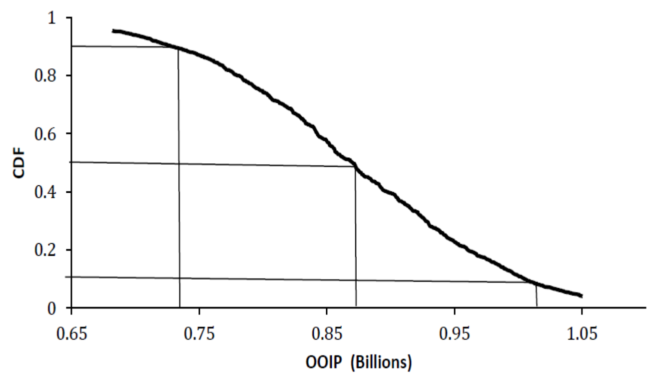

Fig. 4, Reserves curve for Unnamed field

Table 5: Proved, probable and possible reserves values of the fields

Field	Prob.	S_{wi}	B_{oi} (Bbl/STB)	φ	h (ft)	A (Acres)	OOIP (Billion STB)
	P90	0.38	1.15	0.23	69.14	3015.99	0.199
Philus	P50	0.43	1.30	0.26	78.44	3421.79	0.235
	P10	0.48	1.45	0.29	87.16	3801.83	0.266
	P90	0.24	1.39	0.33	34.79	415.59	0.019
Otu	P50	0.27	1.56	0.37	39.11	467.12	0.024
	P10	0.30	1.75	0.41	43.79	523.05	0.029
	P90	0.34	1.01	0.30	382.95	1251.65	0.728
Unnamed	P50	0.38	1.14	0.34	433.10	1415.58	0.871
	P10	0.42	1.27	0.37	482.48	1576.96	1.005

Table 6: Probabilities for estimated oil in place

Field	Estimated OIP (Billion STB)	Probability (%)
Philus	0.21	82.06
Otu	0.02	80.63
Unnamed	0.78	81.04

3.2 Developed Volumetric Approach Based Models Performance

3.2.1 DOE Model Performance

The developed DOE model for estimating reservoir oil in place is presented in Equation 6. Comparing the developed DOE model and volumetric equation estimations of the reservoir oil in place (Fig. 5) resulted in the coefficient of determination (R^2) value of 0.9987. This statistical indicator value implied that the developed DOE model and volumetric equation estimations were very close. This closeness is observed in the data points in Fig. 5 which are located along a unit slope; meaning a good agreement between the DOE model and volumetric equation data [25]. Furthermore, the use of the developed DOE model to estimate the fields (Philus, Unnamed and Otu) reservoir oil in place resulted in about 0.02, 0.21 and 0.75 billion barrels for Otu, Philus and Unnamed field, respectively.

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ISSN 2229-5518

$$
\begin{aligned}
OIP_{DOE} = & -6.9\times10^{-5} - 8.333\times10^{-6}\left(S_w\right) + 4.133\times10^{-5}\left(B_o\right) - 2.986\times10^{-1}\left(\varphi\right) + 1.803\times10^{-4}\left(h\right) - \\
& 1.833\times10^{-5}\left(A\right) + 4.3\times10^{-5}\left(B_o S_w\right) + 2.98\times10^{-1}\left(\varphi S_w\right) - 1.813\times10^{-4}\left(hS_w\right) + \\
& 1.833\times10^{-5}\left(AS_w\right) + 1.31\times10^{-5}\left(\varphi B_o\right) - 7.967\times10^{-5}\left(B_o h\right) + 7.667\times10^{-6}\left(AB_o\right) + \\
& 1.20699\times10^{2}\left(\varphi h\right) - 12.286\left(\varphi A\right) + 1.253\times10^{-2}\left(Ah\right) - 1.309\times10^{-1}\left(\varphi B_w S_w\right) + \\
& 8.067\times10^{-2}\left(B_o hS_w\right) - 7.667\times10^{-6}\left(AB_o S_w\right) - 1.207\times10^{2}\left(\varphi hS_w\right) + 12.286\left(\varphi AS_w\right) - \\
& 1.253\times10^{-2}\left(AhS_w\right) - 52.999\times\left(\varphi hB_o\right) + 5.348\left(\varphi AB_o\right) - 5.199\times10^{-3}\left(hAB_o\right) + \\
& 1.1979\times10^{4}\left(\varphi hA\right) + 52.999\left(\varphi hS_w B_o\right) - 5.348\left(\varphi AB_o S_w\right) + 5.199\times10^{-3}\left(hAS_w B_o\right) \\
& -1.1979\times10^{-4}\left(\varphi AhS_w\right) - 4.640\times10^{3}\left(\varphi hAB_o\right) + 4.640\times10^{3}\left(\varphi hAB_o S_w\right)
\end{aligned}
\tag{6}
$$

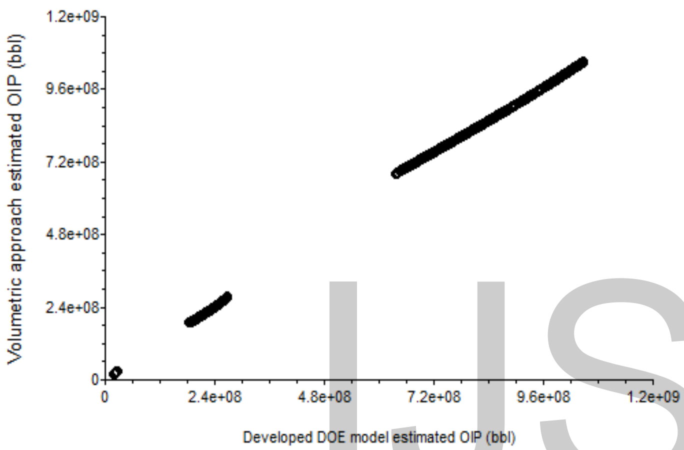

Fig. 5, Comparison of volumetric equation and DOE model estimations

3.2.2 ANN Model Performance

The ANN network training process was stopped at the best validation performance MSE of 1.5327×10^{-9} at 498 epochs (Fig. 6). The performance efficiency of the ANN model is shown on the close trends between the train, validation and test in Fig. 6. This is further indicated in the regression plots obtained for the ANN predicted reservoir oil in place (output) and the volumetric approach estimated reservoir oil in place (target) in Fig. 7. As observed, the model predictions fit perfectly to the volumetric estimations for training, testing and validation sets with correlation coefficients (R) of 1.0. This R-value implies that the developed ANN model predictions were exact as the estimated reservoir oil in place using the volumetric method. Hence, the developed ANN model based on the Levenberg-Marquardt algorithm for predicting reservoir oil in place in normalized form is given in Equation 7;

$$
OIP_{ANN} = \sum_{j=1}^{5}\left\{ purelin\left\{ \sum_{i=1}^{10}\sum_{j=1}^{5} t\an sig\left[\left(S_w j_1 + B_o j_2 + \varphi j_3 + hj_4 + Aj_5\right)_i + b_1\right]\right\}\times Lw_{i,j} + b_2 \right\}
\tag{7}
$$

The variables j_1 through j_5 are input weights to the hidden layer attached to the inputs parameters (i.e., S_{wi}, B_{oi}, φ, h, and A), while Lw_i denotes the weights in the hidden layers to the output neuron. Also, b_1 and b_2 are biases in the hidden layer neurons and output layer neuron, respectively. Thus, these variable values for the developed ANN model are presented in Table 7. The use for this developed ANN model to predict the fields (i.e., Philus, Otu and Unnamed field) reservoir oil in place resulted in 0.2556 billion STB for Philus field, 0.0208 billion STB for Otu field and 0.6303 billion STB for Unnamed field. Besides, the average contribution of the input parameters to the developed ANN model was analyzed based on the obtained connecting weights using Equation 8 established by Maghadem *et al*. [26].

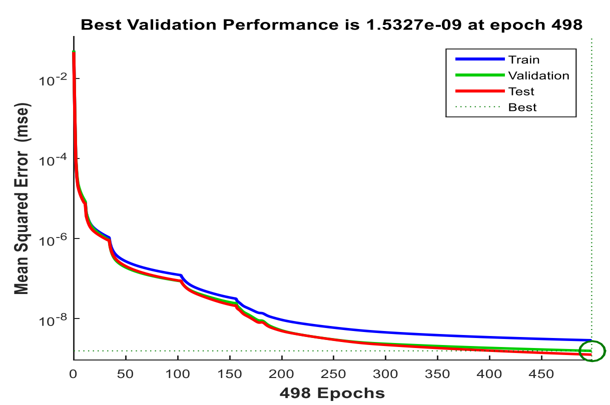

Fig. 6, The ANN performance trends

International Journal of Scientific & Engineering Research, Volume 11, Issue 7, July-2020
ISSN 2229-5518

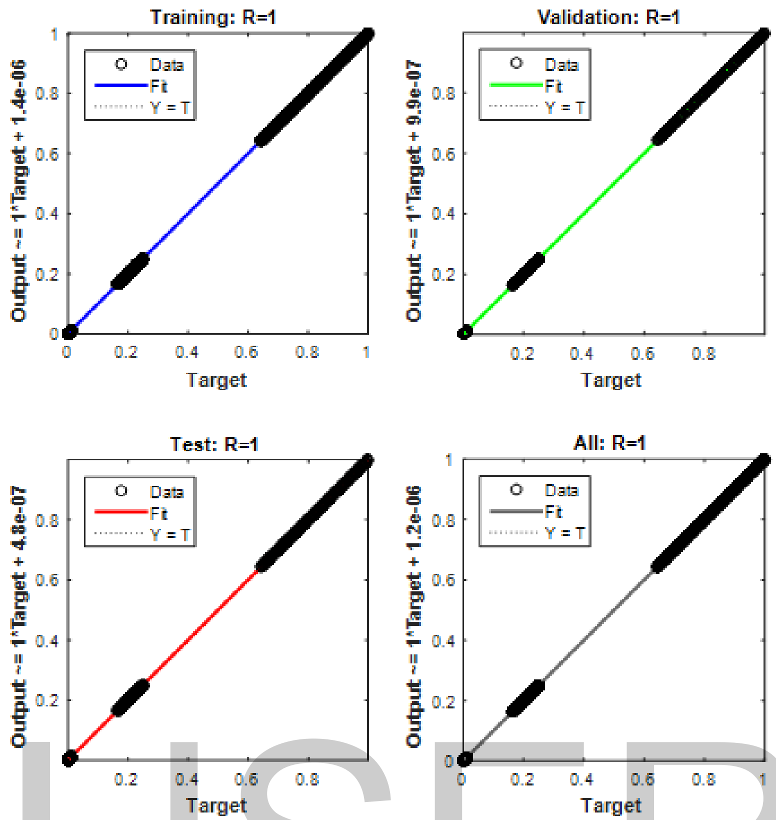

Fig. 7, Scatter plots of the developed ANN model

Table 7: Weights and biases of the developed ANN model

	Input Weights					ILB	HLW	OLB
i	$j_1(S_w)$	$j_2(B_{oi})$	$j_3(\varphi)$	$j_4(h)$	$j_5(A)$	b_1	Lw_i	b_2
1.	1.1019	1.3986	-0.050314	-0.76764	-0.91149	-2.8357	-1.5441	1.4135
2.	-8.0275	-13.3957	-9.4165	-6.0713	-3.9231	14.0896	-6.3234	
3.	-0.71979	1.6998	0.1852	-0.64623	-1.618	-0.87252	-1.1237	
4.	0.73482	-1.8243	-0.33052	1.1927	0.15606	-0.60759	1.3431	
5.	-0.028197	6.0171	4.9851	-0.92821	-2.6103	-2.2352	0.78689	
6.	3.179	0.57464	-0.35229	-1.8833	1.8183	0.68855	1.6549	
7.	0.18869	-1.8583	0.65046	-0.021329	-0.91847	1.1419	0.71446	
8.	-1.3134	-1.5416	0.68438	0.042577	0.85339	-0.80802	-0.54327	
9.	-0.82476	-0.10506	-0.9155	-1.3784	1.1798	-1.7081	-1.973	
10.	-1.4142	-0.010705	0.57949	-0.84038	1.2939	-2.324	-1.3926	

ILB = Input layer biases, HLW = Hidden layer weight, OLB = Output layer bias

$$C_i = \frac{\sum_{j=1}^{n_2} \left| w_{ij} \right|}{\sum_{k=1}^{n_1} \sum_{j=1}^{n_2} \left| w_{ij} \right|} \qquad (8)$$

In the Equation 8, the average contribution of each input parameter i, is C_i, the connection weight from input neuron i to hidden neuron j, is w_{ij}, then n_1 and n_2 are dimensions of the input and hidden layers' neurons, respectively. The result of this analysis is presented in Fig. 8. From the Figure, it is observed that the initial oil formation volume factor (B_{oi}) of the reservoir is the most contributing

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factor (30.51%). Other input parameters: initial water saturation (S_w), porosity (φ), oil column (h) and reservoir area (A) resulted in average contribution factor of 18.82%, 19.48%, 14.78% and 16.41%, respectively. In essence, the ranking of the input variables' average contributing factors on the developed ANN model showed that $B_{oi} > \varphi > S_{wi} > A > h$.

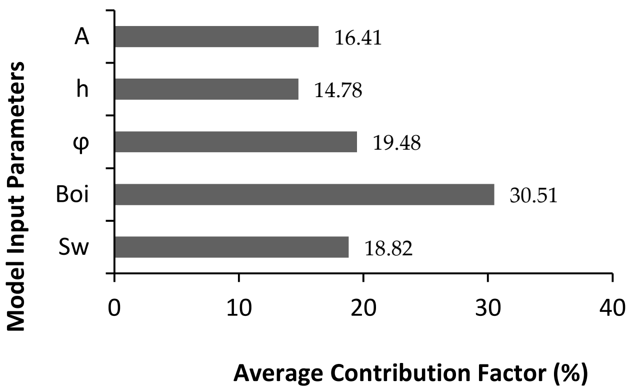

Fig. 8, The developed ANN model inputs average contribution

3.3 Comparison of Developed Models Performance

Table 8 and Fig. 9 present the comparison of the developed models (i.e., DOE and ANN) performance with the volumetric approach equation estimations of the fields' (i.e., Philus, Unnamed and Otu) oil in place. Four statistical indicators, namely, coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE), were used to evaluate the performance of the developed models. The results obtained showed that DOE model had R^2 of 0.9971, MSE of 0.0003, RMSE of 0.0172 and MAE of 0.0640, while ANN model resulted in R^2 of 0.9241, MSE of 0.0079, RMSE of 0.0891 and MAE of 0.0640. These performance metrics indicate that the developed DOE model estimations of the fields' oil in place were closer to the volumetric approach equation estimates than the ANN model. This observation is crystal clear in Fig. 9. The reasons for the good performance of the DOE model over the ANN model are that the developed DOE model was optimized using SOLVER and that it is an estimator not predictor like ANN model. In any case, these alternative models for estimating or predicting reservoir oil in place in the Niger Delta fields look good. However, the applicability of the ANN model, if optimized with optimization techniques like the genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), imperialist competitive algorithm (ICA), etc., will be more robust than the developed DOE model. This is because the ANN model being an artificial intelligence (AI) approach would handle and predict wide ranges of unseen data better than the DOE model. Again, its adaptability in software development would be more useful than the DOE model.

Table 8: Performance indicator of the developed model

Developed Model	Performance Indicator			
	R^2	MSE	RMSE	MAE
DOE	0.9971	0.0003	0.0172	0.0106
ANN	0.9241	0.0079	0.0891	0.0640

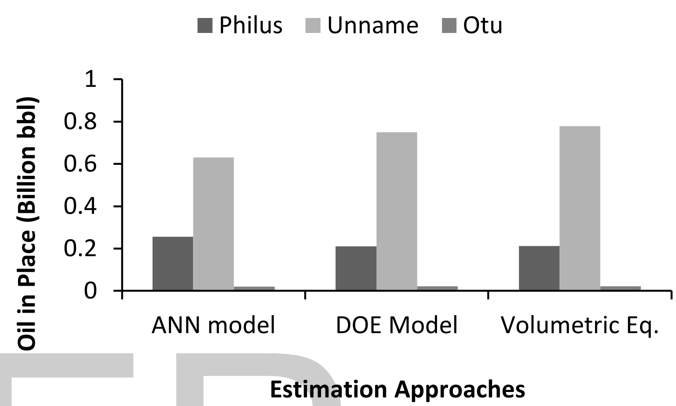

Fig. 9, Comparison the models estimations performance

4 CONCLUSION

The importance of accurate quantification of the volume of oil in the reservoir has led to the continuous development of models and methods that can more accurately predict reservoir oil in place. In this work, Monte Carlo simulation was used to establish reserves of three (3) fields in the Niger Delta and the associated uncertainty in their estimated oil in place based on the volumetric approach. Again, alternative models, namely, DOE and ANN models were developed for estimating reservoir oil in place and the following conclusions can be drawn:

i. the volumetric approach estimated reservoir oil in place is less than its proved reserves but more than its probable and possible reserves;
ii. the associated uncertainty with volumetric approach estimation of reservoir oil in place is between 18% to 20%;
iii. the developed alternative models estimation/prediction of the Niger Delta fields' oil in place resulted in R^2 of 0.9971, MSE of 0.0003, RMSE of 0.0172 and MAE of 0.0106 for the DOE model and R^2 of 0.9241, MSE of 0.0079, RMSE of 0.0891 and MAE of 0.0640 for ANN model; and

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ISSN 2229-5518

iv. for the developed ANN model, the average contribution factor of the input variables was 18.82% for initial water saturation, 30.51% for initial formation volume factor, 19.48% for porosity, 14.78% for oil column and 16.41% for reservoir area.

The developed alternative models for estimating reservoir oil in place looks promising. The good performance of the DOE model over the ANN model is quite interesting; however, its adaptability to handle wide ranges of unseen data remains an area of concern. Therefore, in future, hybridized ANN model should be considered to optimize and improve the prediction performance of the ANN model.

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