

Full Length Research Paper

Probabilistic approach for shale volume estimation in Bornu Basin of Nigeria

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The gamma ray log has over the years provided the conventional means for shale volume (Vsh) estimation. Knowledge of Vsh is used in the prediction of petrophysical parameters like effective porosity and water saturation, which are the input parameters for the calculation of oil in place. Currently, many studies have been conducted on the Bornu Basin of Nigeria, to access its hydrocarbon potential. Unfortunately, the practice of using best gamma ray log value for the computation of gamma ray index, I_{GR} , and subsequently Vsh estimation incorporates huge uncertainty in the estimated volumes. Uncertainty is best captured when estimates are represented in a possible range rather than single value measurements. To the best of our knowledge, this is the first time shale volume has been estimated from the gamma ray log using sampling techniques. The gamma ray log data of the two upper shaly intervals of the NGAMMAEAST_1 well, which penetrates the Gombe formation of the basin, were utilized for this study. The gamma ray log response of the zone of interest is the uncertain parameter in Vsh estimation. A histogram plot of the uncertain log data was used to assume the probability distribution of the data. In the MATLAB platform, Standard Monte Carlo (MC) and Latin Hypercube sampling techniques were used to model the uncertain log response using random numbers. Possible input log data generated from the distribution of the uncertain log data were used in the linear and non-linear models for shale volume estimation to run a series of simulations to determine the possible range of estimates with their probabilities. The Latin hypercube method has shown to be a quick and accurate alternative method to the standard MC method. The approach presented here sets a guideline for the implementation of a probabilistic approach for the volume of shale estimation.

Key words: Shale volume, Monte Carlo, Latin hypercube, sampling techniques, gamma ray log.

INTRODUCTION

The government of Nigeria has currently reopened its interest in exploring the hydrocarbon potential of the Bornu basin. This basin forms a part of the huge Chad basin. Earlier exploration activities were unsuccessful

due to non-commercial discoveries. However, the discovery of commercial quantities of hydrocarbons in other areas of the basin lying in countries like Chad, Niger and the Central African Republic has revived the

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the government's commitment to exploring the basin. The stratigraphy of the basin is made up of different formations (Bima, Fika, Gongila, Kerri-Kerri, Gongila, Yolde, Chad) composed of sandstone, shale, siltstone, and limestone (Adekoya et al., 2014). Detail description of the basin can be found in works published by (Ali and Orazulike, 2011; Hamza and Hamidu, 2012). Over the past few years, there have been intensive studies on various areas of the basin. Ola et al. (2017) evaluated the potential of the source rock at the south-western section of the basin using rock samples from three different wells. The authors identified the area to be predominantly gas-prone with oil shows in one of the wells. Similar results were obtained by Obaje et al. (2004) who studied the quality of source rock using samples from four different wells. Obaje et al. (2004) in their work, identified over 80% of samples from the wells to contain a total organic content above 0.5 wt.%. Mohammed and Tela (2012) used the particle size and the depositional setting of sediments to determine the hydrocarbon potential of the basin. Sanusi and Mickus (2014) used geophysical data to study the structural configuration of the basin while Adepelumi et al. (2011) did a petrophysical analysis of the Gombe formation.

Shale volume (V_{sh}) estimation is a significant step in formation evaluation. V_{sh} is an expression of the fraction of the total amount of clay and other particles such as silt to the total rock volume (Szabó, 2011). The estimated V_{sh} are used in the prediction of petrophysical parameters like effective porosity and water saturation from which the hydrocarbon in place can be estimated (Airuwalli and Alwaheed, 2004). Knowledge of the reservoir shaliness guides in the evaluation of the rock's quality (Ali and Orazulike 2011). Though V_{sh} estimation can be done using data from the density-neutron log, spontaneous log, the resistivity log, and other methods, the gamma ray log has served as the conventional means of computing the shale volume. Equation 1 is the linear model for V_{sh} estimation using the gamma ray log. The model estimates the gamma ray index, I_{GR} , of the shaly interval and assumes it to be the V_{sh} of the interval (Hamada, 1996; Adam and Bashar, 2017).

$$I_{GR} = V_{sh} = \frac{G - G_{cleansand}}{G_{shale} - G_{cleansand}} \quad (1)$$

where I_{GR} is a gamma ray index, V_{sh} is the volume of shale, G is gamma ray reading in the zone of interest, $G_{cleansand}$ is gamma response in clean sand and G_{shale} is the gamma ray response in shaly or clay bed.

Nonlinear model for V_{sh} estimation

The linear model approach assumes the formation to contain only shale and clay minerals. This assumption tends to overestimate the shale volume in zones

containing other radioactive minerals. A number of non-linear models defined for certain formation ages and geographic areas have been formulated to mitigate the uncertainties associated with the linear model (Worthington, 2008; David et al., 2015). The Larinov models for tertiary and older rocks and the Steiber and Clavier models are given in Equations 2 to 5.

Larinov (1969) for tertiary rocks

$$V_{sh} = 0.083(2^{3.7I_{GR}} - 1) \quad (2)$$

Larinov (1969) for older rocks

$$V_{sh} = 0.33(2^{2I_{GR}} - 1) \quad (3)$$

Steiber (1970)

$$V_{sh} = \left(\frac{I_{GR}}{3 - 2I_{GR}} \right) \quad (4)$$

Clavier (1971)

$$V_{sh} = 1.7 - \left[(3.38 - (I_{GR} + 0.7)^2) \right]^{\frac{1}{2}} \quad (5)$$

It can be seen that these non-linear models rely on the computed I_{GR} from the linear model as input for their prediction. However, the common approach of using best gamma ray log value of the zone of interest for I_{GR} computation incorporates huge uncertainty in the estimated I_{GR} , which is, propagated through these non-linear models and hence undermining their accuracy. The conventional approach for V_{sh} estimation used in the Bornu basin and the petroleum industry at large has been deterministic and performed under huge uncertainty. This has resulted in huge discrepancies in published works. This paper seeks to illustrate the role of sampling techniques in mitigating the uncertainty in the input parameters and to recommend their application in the volume of shale estimation in the Bornu basin and the petroleum industry at large.

Standard Monte Carlo and Latin hypercube techniques

The Standard Monte Carlo (MC) and Latin Hypercube Simulation (LHS) are methods that provide a stochastic approach for uncertainty evaluation. In these techniques, the uncertain parameter is modeled using random numbers. In this way, possible input values obtained are used in a series of simulations to determine a range of estimates with their probabilities. One main advantage of the MC method is that it is independent of the number of input random samples (Alkhatib and King, 2013).

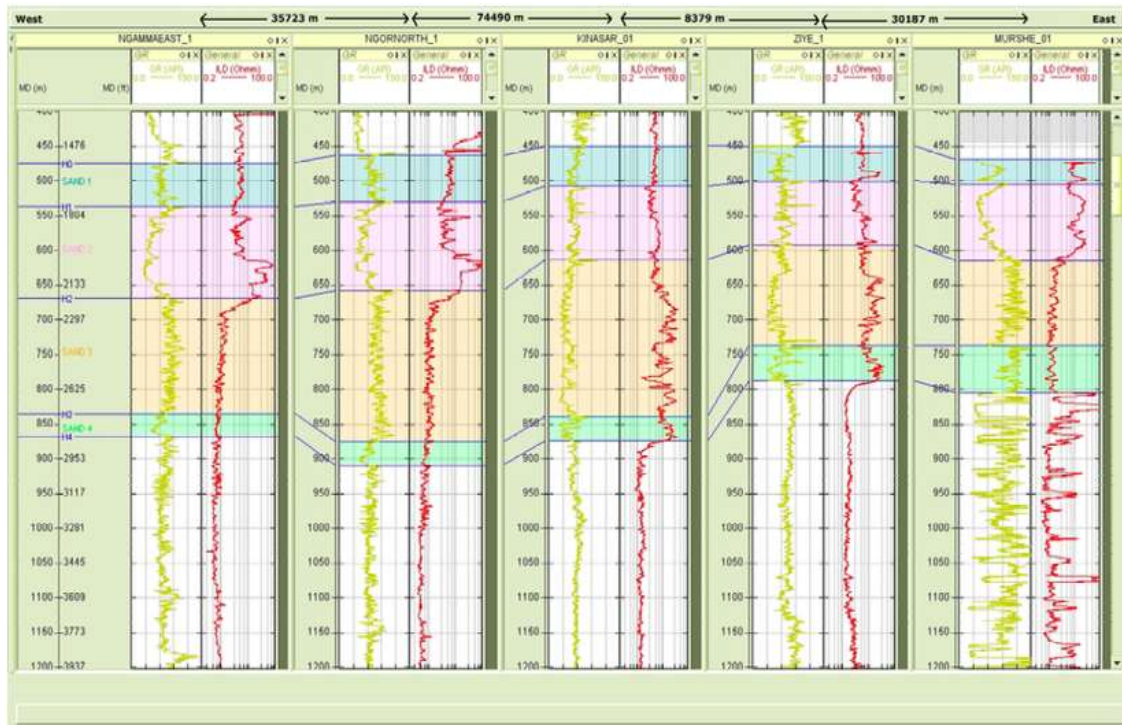


Figure 1. Log data of NGAMMA_1 well.

Table 1. NGAMMAEAST_1 Well Log Data.

Sand Unit	Thickness (m)	K (md)
Sand 1	62.30	9986.74
Sand 2	131.63	18948.68

K = Permeability.
 Source: Adepelumi et al. (2011).

However, it requires large computational times to achieve accuracy due to its low convergence rate, with a convergence rate of $1/\sqrt{N}$, where N is the number of paths or realizations (Xiu, 2007). Also, due to its randomness, it sometimes results in clustering. Unlike the Standard MC, the LHS is a controlled randomization technique. The distribution of the input data is partitioned into even intervals of equal probability. A sample is selected from each interval and used in repeated simulations. The process requires less iteration to achieve accuracy (Nathanail and Rosenbaum, 1991).

METHODOLOGY

Data

This illustration was done using the NGAMMAEAST_1 well, which penetrates the Gombe formation of the Bornu basin. The log data, obtained from Adepelumi et al. (2011), was made available by the

Nigerian National Petroleum Corporation. The log is given in Figure 1. The properties of the zone of interest for this study are reported in Table 1.

Procedure

Uncertainty evaluation using the sampling techniques for I_{GR} and V_{sh} computation was illustrated using only the top two shaly intervals of the well; Sand 1 (depth of 475-540 m) and Sand 2 (depth of 540-670 m). From Equation 1, the gamma ray response in the clean sand and that in the shaly interval are assumed constant; 30 and 148 American Petroleum Institute (API) units respectively. The gamma ray log value in the zone of interest is the uncertain input parameter in the volume of shale estimation models. The first step was to determine the distribution of the log data in the zone of interest. For Sand 1, the thickness was divided into 10 equal intervals and three log values were picked from each interval. A histogram of the sampled data was then generated to determine the distribution of the log values. The procedure was repeated for Sand 2 but with 20 divisions. The distributions of the input log values for both sand intervals were assumed to follow the normal distribution, (Figure 2). The probability and cumulative density functions of the

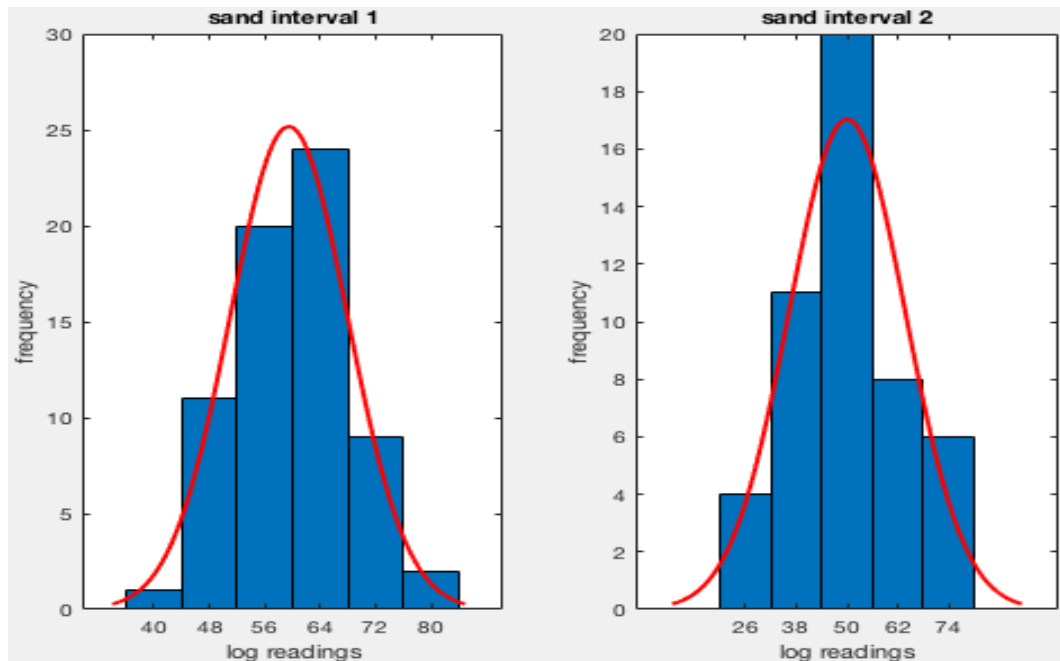


Figure 2. Distribution of Input Data for Sand 1 and 2.

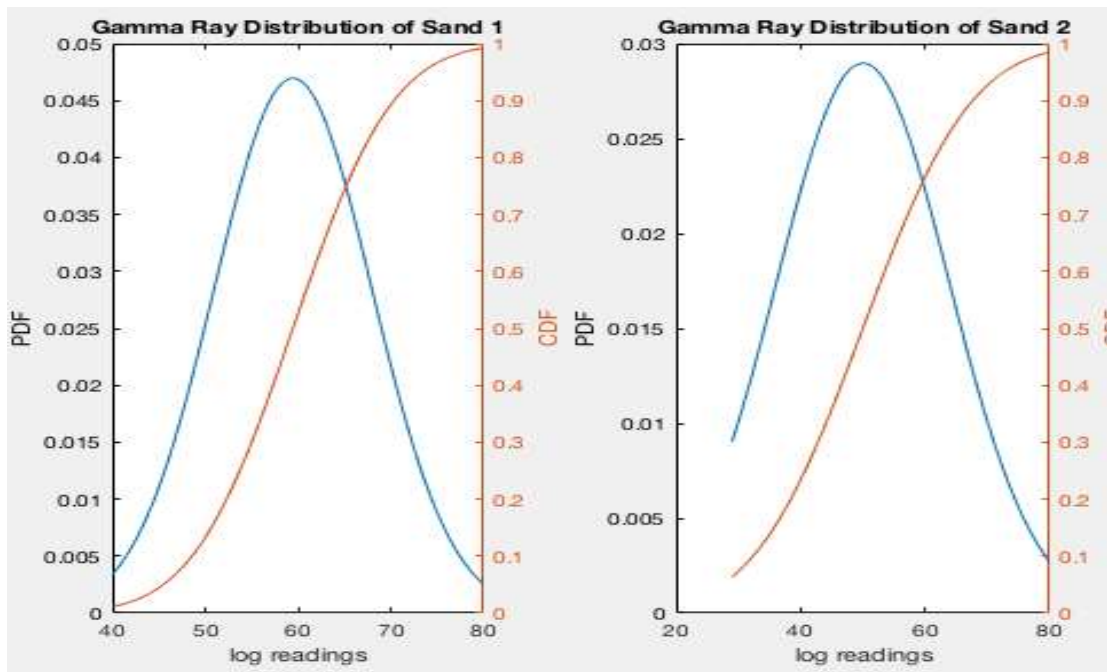


Figure 3. Density and cumulative density function plots of input data.

input data are plotted in Figure 3. To implement probabilistic techniques, the log data is modeled as random variables. Monte Carlo (MC) and Latin hypercube sampling methods were used to sample from the cumulative distribution of the uncertain input log data. In the case of the LHS technique, the cumulative distribution function of the input log data was divided into 5 intervals of equal

probability from which a sample was taken from each interval. These sampled data were then used in the linear model to determine the shale volume of the intervals. The P10, P50, and P90 of the estimates were then computed. The generation of the cumulative distribution and probability density functions of the log data, sampling and simulation were done using the MATLAB

Table 2. Monte Carlo simulation for sand 1.

Percentiles	Vsh				
	Linear (%)	Larinov tertiary (%)	Larinov old (%)	Steiber (%)	Clavier (%)
P10	16.2	4.0	7.6	6.0	7.7
P50	25.6	7.5	12.5	10.0	12.6
P90	34.9	11.7	18.3	14.8	18.6

Table 3. Monte Carlo simulation for sand 2.

Percentiles	Vsh				
	Linear (%)	Larinov tertiary (%)	Larinov Old (%)	Steiber (%)	Clavier (%)
P10	5.0	1.5	2.7	2.2	2.7
P50	19.2	5.6	9.6	7.7	9.7
P90	35.0	12.5	19.3	15.7	19.6

Table 4. Latin hypercube simulation for sand 1.

Percentile	Vsh				
	Linear (%)	Larinov tertiary (%)	Larinov old (%)	Steiber (%)	Clavier (%)
P10	15.7	4.1	7.3	5.9	7.4
P50	25.0	7.5	12.4	10.0	12.6
P90	34.2	11.7	18.2	14.7	18.5

Table 5. Latin hypercube simulation for sand 2.

Percentile	Vsh				
	Linear (%)	Larinov tertiary (%)	Larinov old (%)	Steiber (%)	Clavier (%)
P10	1.3	0.3	0.5	0.4	0.5
P50	19.0	5.2	9.0	7.2	9.0
P90	36.7	13.0	20.0	16.2	20.0

language.

RESULTS AND DISCUSSION

Determination of Vsh requires the estimation of I_{GR} . For a given I_{GR} , the Vsh is then estimated using different models. The conventional deterministic approach for shale volume estimation is based on user experience, resulting in huge uncertainties. Sampling techniques provide a means of minimizing the error associated with the estimation of the I_{GR} and hence Vsh. Two zones of the Gombe Formation in the Bornu Basin, penetrated by the NGAMMAEAST_1 well have been used to illustrate the significance of sampling techniques in predicting the shaliness of a formation. The performance of two sampling techniques has been studied. The Monte Carlo sampling is based on random sampling from the

distribution of the uncertain input data. The MC method requires large iterations to achieve accuracy due to its slow convergence rate. The results in this paper are based on 2000 samples. Over the years, there have been various improvements to the MC technique. LHS is a new technique that tends to approach MC accuracy using fewer data points. Unlike in the deterministic method, which yields single value measurements, probabilistic techniques yield a wide range of estimates with their associated probabilities. These values represent optimistic and pessimistic estimates, which are critical in decision making. The P10, P50 and P90 values for the linear and non-linear models computed from the realizations of the Monte Carlo simulation have been reported in Tables 2 and 3 for Sand 1 and 2 respectively. Similarly, the results from the LHS are reported in Tables 4 and 5 for Sand 1 and 2 respectively. It is observed that

the computed P10, P50 and P90 values are similar for both sampling techniques for Sand 1, though in the Latin hypercube method fewer data points were used. The LHS, therefore, provides an efficient alternative to the conventional MC method. For Sand 2, the computed P50 and P90 using both techniques yielded similar results. However, there were huge variations in the P10 values for all models. Monte Carlo results are reliable in such situations as it uses more data points.

Comparing the results of this study to those in literature for the same well and sand intervals, it was observed that a number of authors have deterministically computed the I_{GR} and subsequently V_{sh} . In highly heterogeneous formations, the errors associated with this approach are substantial. Results from this study have shown that the linear model for the computation of shale volume, which assumes the V_{sh} to be linearly proportional to the I_{GR} , overestimates the shale volume. For a given I_{GR} , it is observed that the Larinov model for older rocks and the Clavier model give similar results while the Larinov model for tertiary rocks yields the least estimates.

Conclusion

This work outlines the approach in using sampling techniques in predicting the gamma ray index and subsequently the shaliness of sand intervals in the Bornu Basin of Nigeria. The following conclusions were made:

- (i) The conventional deterministic approach in shale volume estimation results in huge errors propagated through the input parameters.
- (ii) The probabilistic approach mitigates the uncertainty in the estimate by providing a possible range of estimates with their associated probabilities unlike the single value estimates of the deterministic approach.
- (iii) The Latin hypercube technique is a quick approach that provides an efficient means of sampling and uncertainty analysis using fewer data points.
- (iv) The linear model overestimates the shale volume.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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