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Prediction of properties of reservoir using Artificial Neural Network and Monte Carlo Simulation

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Abstract
Two methods for forecasting reservoir distribution are used: Monte Carlo Simulation and Artificial Neural Network. The data used in this research was obtained from the drilling sheet report of the Efe04 well located in the Northern Niger Delta Depobelt. The operator released the data set of the Efe field. Amukpe well data from the Amukpe field was also used as part of the test data to see how the model works on different fields. To minimize uncertainties, only the surface drilling parameters are used for the model. Mode of operation (rotation or sliding), Torque, Surface Revolution, Flow rate (gallons per minute), Stand Pipe Pressure, Revolutions per Minute, hole size. When reservoir distribution can be predicted, it is extremely beneficial since it increases exploration accuracy and lowers costs by delaying the next round of exploration. Geostatistics, on the other hand, is rarely used in areas with few wells drilled. A new technique called Geology Driven Integration Tool (GDI) has been developed to estimate reservoir parameters when just a few wells are available. Due to the lack of well data and regional geological constraints in the GDI model, several pseudo-wells are constructed by Monte Carlo Simulation to make up for the deficiency of a few real wells. They can also be used to create fake seismograms. To determine the weighting factors that link the selected seismic attributes to the given reservoir features, the appropriate seismic attributes and the given reservoir parameters are input to the Artificial Neural Network (ANN). In the end, the ANN is trained on all of the seismic data in the area and then used to estimate reservoir property distribution. In addition to the areas that have already been explored, the estimated results suggest exploring the southern portion of the Efe field and the northern portion of the Efe field as potential prospect locations. In the southern half of the Amukpe field, the gas zone's net thickness is expected to rise to 27 meters, thanks to increased porosity of 27%. North of the Efe field, a 15-25-meter-thick porosity-rich reservoir is predicted to be distributed.

Keywords: Monte Carlo Simulation, Artificial Neural Network, Northern Niger Delta Depobelt

1. Introduction

Geostatistics or other methods have been used in recent years to estimate reservoir characteristics because the study can help increase exploration accuracy while also saving money on subsequent exploration [1, 2]. It is a current method. A correlation between seismic parameters and reservoir characteristics cannot be established until several wells have been completed, whether in the early stages of exploration or later on. De Groot-Bril Earth Science in the Netherlands has created a new technique called Geology Driven Integration Tool (GDI). In GDI, Monte Carlo Simulation and Artificial Neural Network are utilized for the creation of fictitious wells and the detection of the association between reservoir features and seismic attributes based on the factual well data and regional geological restrictions [3]. To determine the lateral distribution of reservoir parameters, we used the GDI approach in two locations. One of them is Amukpe. Efe field is in the Sea of Nigeria, while Northern Central is Nigerian. The region to the east of Nigeria. The thickness and quality of the reservoir have not been quantified even though 2-D and 3-D seismic investigation has been carried out in the two regions, respectively. Since there are either too few or an excessive number of known control points in the first situation, using the usual geostatistics method is challenging. Concentrated in the latter scenario, making it difficult to establish a link between reservoir characteristics and seismic qualities. For estimating reservoir properties, Monte Carlo Simulation works best in this environment. Because we only have limited factual well data, the goal of our research is to find a link between reservoir features and seismic reaction using Monte Carlo simulations and artificial neural networks powered by GDI. and geological knowledge and to predict the distributions of reservoirs and then, further, to find out potential areas for the future development of the two fields.

2. Geological background of study areas

Although the reserve may be critical, the Pantai Pakarn Timur gas field was identified in 1979 and the shallow gas zone (referred to as the 1,275m zone) becomes a significant development target. Even though the field has had seven wells drilled since 1979, only two of them have been found: PPT-5 and the Efe field. In the middle section of the field, a few development wells were sunk, and a 3-D seismic survey was carried out. Pliocene oil and gas reservoir zones include the Lower and Upper 2,100m zones, 1,900m zone, 1,500m zone, and so on. The investigation will focus on the Lower 2,100-meter and Upper 2,100-meter zones, which are considered the main reservoirs. The results of fossil foraminifera and lithofacies investigations on the core samples suggest that the reservoir sandstones deposited as turbidite beneath the upper to the upper-middle bathyal environment, according to this hypothesis. Also, they're thought to be growing from the south to the north [4, 5]. Despite this, there is no way to know how sandstone qualities like thickness and porosity are distributed in the northern section of the region because no wells have been dug there. The eastern limb of the fold has several thrusts running perpendicular to its axis. Study the 1,275m reservoirs using PPT-6. A 2-D seismic study was carried out in the vicinity and gas columns of 5m+ and 19m were discovered in the two wells. There is a tiny fault between PPI -5 and PPT -6 on the seismic segment. However, it can be assumed that the reservoirs between the two blocks communicate with one another, therefore the same gas/water level at -1,260 m is understood. It appears in the southern region where we had previously documented a prominent AVO event that the broad and higher domal structure is present [4]

3. GDI method

3.1 Monte Carlo Simulation and Geological Framework

Seismic qualities come in a wide variety of forms, some of which might be interpreted as a reaction to shifting subsurface rock properties. The properties of amplitude are the simplest to comprehend. Changes in porosity, lithology, fluid contact and bed thickness are all reflected in these data points [7, 8]. For the past two decades, technologies like bright spot and AVO have been successful in the hunt for hydrocarbons. There are links between seismic attributes and reservoir properties that need to be found to assign property values to seismic interpretation in general. An attribute-to-reservoir property relationship that is statistically significant can be utilized to estimate the value of properties away from the well control area in seismic survey results. However, the issue is that there are only a few well data that may be utilized as sample data to identify the statistical connection. Because there are so few wells, a method was devised to produce fictitious ones using Monte Carlostatistics To approximate the solution to mathematical or physical problems statistically, the Monte Carlo approach uses sampling-based on probabilities. When compared to the standard approach, this strategy has two key advantages. As a first benefit, the algorithm can be guided by principles derived from geological reasoning. The second is that each of the stochastic variables can have severe limitations imposed on it. Constraints placed on the top and lower bounds of probability density functions are referred to as hard constraints. It is against this boundary that stochastic realization is measured. Hard requirements must be met before a variable can be used. If they are not, they can be redrawn or accepted. Details of the Monte Carlo simulation can be found in [6]. For the most part, geological interpretation relies on a variety of facts and expertise to make sense of the findings. A framework for integration brings together geological data, good logs, and knowledge in GDI. We can assign a rock type to each lithological unit by using a hierarchical ordering scheme for objects and geological units such as stratum units, substratum units, and lithological units in the framework. The lithological units in our illustration are divided into two categories: seaLwaste and reservoir type. The simulation technique simulates vast hydrocarbon columns by using Seal as a seal. Fluid can be found in reservoir rocks. We can track reservoir changes at various scales thanks to the integrated data. The combined data is then used to build a large number of pseudo-wells with varied stratigraphic compositions and well log responses, but no geographical information. A realistic picture of the variance in and around the target reservoir zone is provided by these fictitious wells. Using a wavelet generated from real seismic recordings of study locations, the synthetic seismic response is calculated for each of the simulated pseudo wells. We'll have a dataset with integrated stratigraphy, logs, and seismic responses as a result of this approach.

3.2 Artificial Neural Network (ANN)

Artificial neural networks are then employed to discover the link between reservoir features and seismic attributes. Promising computer technology is known as the artificial neural network (ANN) or connection model has arisen in the previous decade and has found application in a wide range of scientific and technological disciplines. As a result, it is well-suited for handling challenging tasks like character recognition. An ANN is a non-linear dynamic system that learns to recognize patterns with the use of certain sample data during the training process. In GDI, three different ANN training models are offered. In the supervised mode, the Unsupervised Vector Quantiser network and Multilayer Sperceptrons are employed, whereas, in the unsupervised mode, the Radial Basis Function and Multilayer Sperceptrons are utilized. The GDI's ANN models can be trained using a variety of methods. Most people have heard of back-propagation. Back-propagation ANNs typically have three layers: an input layer with multiple input nodes, an output layer with one or more output nodes, and at least one hidden layer with multiple nodes. The weights connecting nodes in neighboring layers are originally randomized. Despite this, there aren't any connections between any of the nodes in a layer. The data is fed forward from one layer to the next. The equation represents the basic algorithm of an ANN.

$$\mathbf{y(x) = \Sigma\ w_i f_i(x)}$$

in which x is the input vector (seismic attribute) of the neural network, y(x) is the output vector (reservoir property), and fi(x) is the basic function. To minimize the error between the calculated and desired output values of the training data, the learning algorithm automatically adjusts the connection weights. In addition to Stephen's 2018 paper, Shultz *et al.* (2018a. 's b) [7] work on neural networks can be found in the references below.

4 Application of GDI method in Amukpe field and Amukpe field

4.1 Establishment of the integration framework

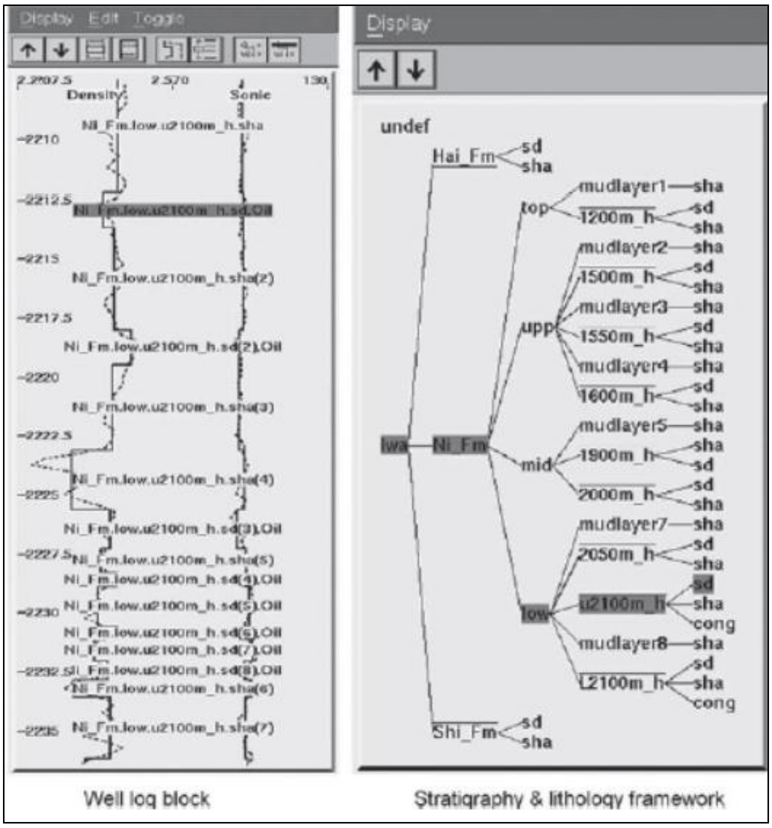


Fig 1: Chart Integration of Amukpe Field

Before creating simulated wells, the integration framework, which combines various geological data, must be established. It is a generic description of the study area's stratigraphy, lithology, well logs, and other geological information that makes up the integration framework These geological framework units have properties and quantities established by researchers and are made up of a small number of geological objects. It is possible to use the integration framework to govern the creation of pseudo wells by using it as a stratigraphy-geology model of the study area. As demonstrated in Fig. l, an example from the Efe field based on the analysis of stratigraphy and factual good data, we developed an integration framework in this study. The framework is defined as follows in this example: There are three primary units defined from geological and log data, namely Hai Fm, Ni Fm, and Shi Fm. The three major units correlate to the research area's stratigraphic formations and dictate the order in which stratigraphic units occur in fake wells. The major simulated unit, Ni Fm, is separated into four portions based on sedimentary order: upper, medium, and lower. Seismic analysis data has divided the top, upper, middle, and lower portions into various zones

or subunits. Since conglomerates found in the Upper 2,100m and Lower 2,100m zones have substantial seismic refraction, most subunits are assigned two lithological units, while target zones are assigned three. Reservoir or waste is the name given to these lithological units. Within the component to be assigned, any of the lothological units might appear in any sequence, can recur, or even be absent altogether Reservoir sandstone units are the only ones with gas-bearing characteristics. When it comes to IwafuneOki, the property is mostly attached to sandstones in the Lower and Upper 2, lOOm zone, whereas in Amukpe field, the property is only attached to rocks in the 1,275m zone.

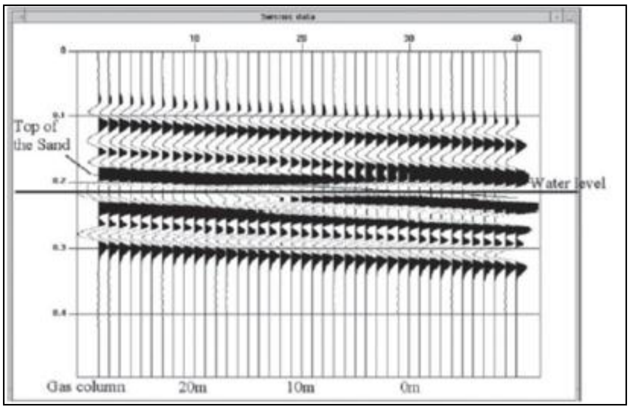
4.2 Pseudo well simulation

Since available wells are either sparse (as in the PPT field) or overly concentrated (as in the research areas), using solely factual well data is insufficient for demonstrating the relationship between reservoir features and seismic parameters in those areas (IwafuneOki field). To be sure of the connection, we'll need to collect more data. First, we created sets of fake wells based on simple models (Model 1 to 3) in which just one framework unit variable was altered to see how reservoir variables affected seismic features. Sensitivity simulations are another name for these simulations. As a next step, we employed Monte Carlo simulation to create pseudo wells with a higher degree of realism by altering numerous variables at once. To find the tl1e relationship, these pseudo wells are employed.

Model: Changing the height of a gas column (Fig. 2)

Amukpe field is an example of this. Changes in reservoir parameters are made from the average values of the factual wells (i.e., 20m thick sandstone with 25 percent porosity and 40 percent water saturation) to the gas column (now 20 w instead of 20 m). Pseudo-well synthetic seismograms are created.

As can be seen in Figure 2, there was a seismic polarity shift near the 1,275-meter sandstone's summit. When the gas column is thick enough, the tops of gas sandstone correspond to black peaks, whereas the tops of gas sandstone or water sandstone that are much thinner become white troughs. It is necessary to meticulously track the interpretation of the top of gas sandstone on the seismic section since it does not always follow the same peak. Due to the thinness of the gas sandstone layers, this is known as 'Tuning



Model 2: adjusting the thickness of gas sandstone (Fig. 2)

Here's an example from the Amukpe field. All that is modified in thickness is from 100 meters to zero meters, and all other parameters are left at the average levels found in genuine wells.
The lower 2100 m zone corresponds to black peaks when zone thickness is thicker than 60 m, but the peaks vanish when the zone thickness is thinner than 60 m (see Fig. 3). Amplitude, phase, and frequency shifts.

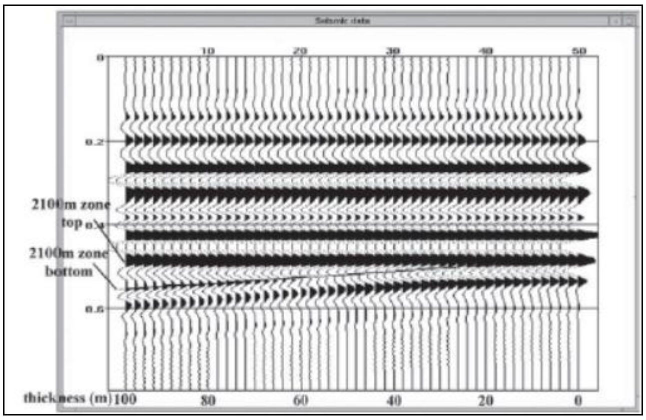


Fig 3: Reservoir Zone thickness changes

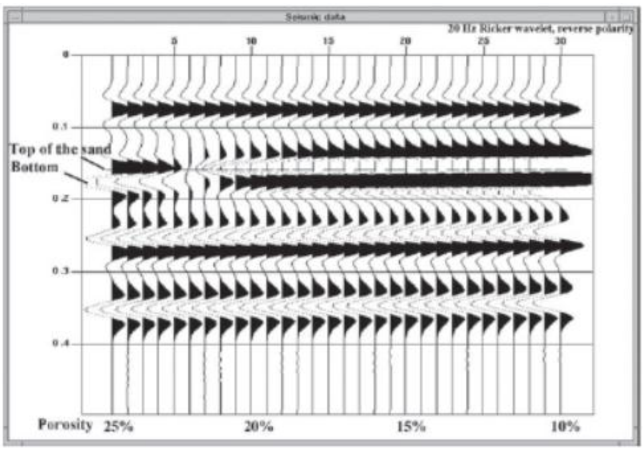


Fig 4: Porosity change of gas sand

Amukpe field is an example of this. The porosity of the 20-meter-thick gas sandstone decreases by 25% in the model. The water saturation has been set at 40%. Gas sandstone only exhibits the black peaks at the top when it has a porosity of 23% or above, according to the simulation. According to brilliant spot phenomena on the seismic section during culmination, there is above 23% porosity in this gas sandstone in the entire area.

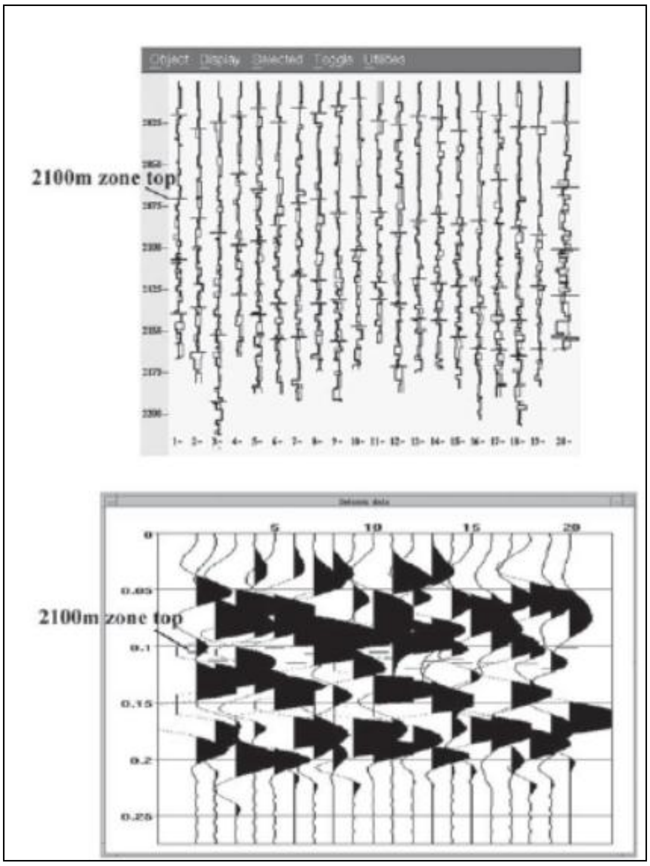


Fig 5: Monte Carlo Simulation

The Monte Carlo method is a sampling procedure based on probabilities to estimate statistically the solution to mathematical or physical problems. It's been put to good use in solving a wide range of issues. Geographical applications with a geoscientific focus. For example, the approach is used to estimate reserves and to evaluate prospects. In fig 5, when simulating genuine wells or 1-D stratigraphic profiles in GDL, the Monte Carlo approach is utilized to simulate physical attributes related to the profiles but without spatial information. The simulated wells are thought to be realistic reconstructions of the subsurface (de Groot *et al*., 2019). We can regulate the simulation and construct only believable pseudo wells by providing geological limitations to the simulator. To make up for the poor state of a few wells In the two research locations, we use Monte Carlo simulation to produce 500 fictitious wells with different stratigraphic compositions and well log responses. For the 1,275m zone in the Amukpe field, the Monte Carlo simulation uses factual well data and other geological knowledge to change thickness, porosity, and the reservoir gas column simultaneously and stochastically. For the 1,100m zones in the Efe field, the Monte Carlo simulation only changes thickness and porosity because the gas column data are unavailable. This is because modifying more than three or two attributes would make forming the relationship more complex. Because water saturation has the same influence on seismic features as porosity and is difficult to discern, it is set at 40% in the Amukpe field, one of the most critical reservoir properties. PPT field 2-D seismic records or Efe field 3-D seismic records are used to create synthetic seismograms for the pseudo-wells. In this manner, we produce synthetic and pseudo-well data sets for each research region, where stratigraphy, well logs, and seismic responses are all combined into one integrated whole. The lithological features and seismic attributes are then extracted from the synthetic seismogram dataset and the pseudo well dataset, respectively, which are later employed as sample data in the training of a neural network.

4.3 Training Neural Network

To anticipate reservoir properties on the side, we utilize a model called the Multi-layers Perceptrons (MLP). The Multi-layers Perceptrons Model makes use of the learning process back-propagation. Sample data from real or fake wells, as well as synthetic seismic responses, were used to train an artificial neural network to learn the nonlinear model. Afterward, we apply the newly-trained ANN to the entire seismic volume to generate reservoir property predictions on the side where no well is present.

Examples of neural networks from the Efe field and Efe field and their performance as trained by pseudo wells created by Monte Carlo simulation are shown in Figures 6 and 7. A total of 10-12 seismic attributes were used in these examples, with just 1-2 reservoir properties (such as sandstone thickness and porosity) being used as outputs. To minimize the difference between the ANN's predicted values and the actual values obtained.

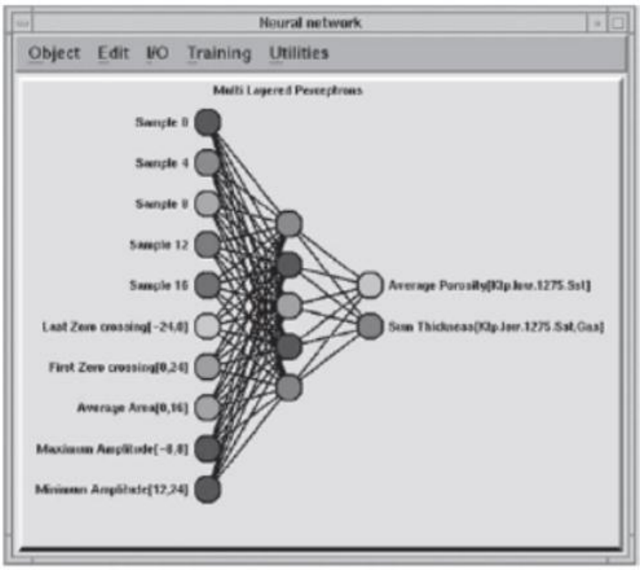


Fig 6: Neural Network Layer

The synthetic seismograms datasets are used to cross-plot the seismic attributes extracted from them with reservoir properties extracted from the pseudo wells, and then the seismic attributes with good relationships to reservoir properties are selected as inputs for the ANN training. This way, we can see how reservoir properties change over time. Concerning their contribution to the output, each node is represented in grayscale, with darker nodes having a greater contribution. Figures depicting network performance demonstrate the relationship between estimated value by neural network and real value by displaying normalized RMS values and correlations between those two sets of values. The better the reliability of a neural network, the smaller the root-mean-square error must be. A substantial correlation between gas column height and seismic features suggests that predictions are accurate, whereas a weak correlation exists between sandstone porosity and seismic attributes in Amukpe, suggesting that predictions aren't as accurate there (Fig. 6). As can be seen in Fig 6 these neural networks were trained using pseudo wells generated by a Monte Carlo simulation in Amukpe and Efe fields, respectively. To illustrate, we used 10-12 seismic parameters as inputs, with the outputs consisting of 1-2 reservoir properties (such as sandstone thickness and porosity). When training an ANN, we cross-plot seismic attributes from synthetic seismograms against reservoir properties from pseudo wells to reduce error. We then select the seismic attributes that have a good relationship with reservoir properties and that reflect changes in reservoir properties as training inputs for the ANN. The ANN can then use these selected seismic attributes as inputs. Since gas column height and seismic attributes have a good correlation, this suggests that the prediction result is reliable; however, sandstone porosity has a weak correlation with seismic attributes, which suggests that the prediction results in Amukpe are less reliable (Fig. 6).

4.4 Applying neural networks to real seismic records

The trained neural networks are applied to the 2-D seismic data of the Efe field and the 3-D seismic data of the Efe field, respectively, to get the distribution of target reservoir attributes along the 2-D seismic lines and in the 3-D seismic areas

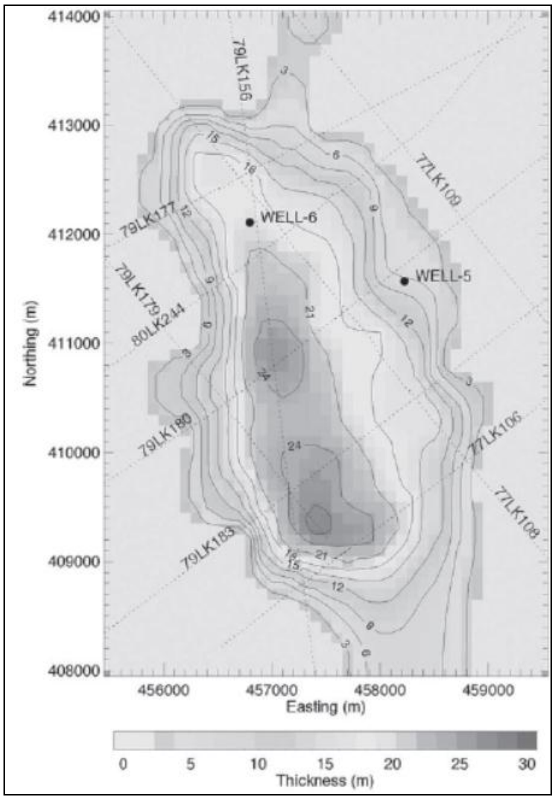


Fig 7: Gas column height derived from Artificial neural network and Monte Carlo simulation

The gas sandstone in the Amukpe field thickens (up to 27m) to the south as predicted in the study The Amukpe field's gas reserves can also be calculated using the final prediction results of the thickness and porosity of the gas sandstone.

Because they may be intercalated with thin waste layers that are inconsequential, the thickness of gas sandstone is regarded to be net values and the estimated porosity is averaged within the net pay zone. By adding up the gas volume at each grid point, you can easily figure out how much the reserve is. In comparison to previous estimates, the new research is over 50 percent larger at 110 BCF

5. Conclusion

For the Efe field in Nigeria and the Amukpe field, we apply Monte Carlo Simulation and Artificial Neural Network to review reservoir distribution and identify future development regions. The new well was drilled in the Amukpe field at the location recommended by this research. The outcome is very close to what we predicted (27 m of prediction versus 24 m of observation). As a result of our research, we've come to the following conclusions: Traditional approaches have a tough time establishing a link between lithological properties and seismic reactions when real well data are scarce or concentrated. Monte Carlo Simulation can help in these situations. The lack of sample data can be mitigated to a large extent using the simulated pseudo-wells. It was utilized to forecast reservoir features in the Amukpe field and Efe fields by simulating real-world data. According to our findings, the seismic responses of various pseudo-wells can be predicted using theoretical reservoir modeling by varying reservoir properties such as the net sandstone thickness and porosity (among other things). Seismic responses alter when reservoir parameters change, according to the estimates. It was found that in the Amukpe field and the Efe field, reservoir characteristics and seismic qualities correlate when using neural networks trained on data from fake wells and their simulated seismicograms. For future research and development in those two locations, the correlations were applied on genuine seismic data to forecast reservoir thicknesses and porosity distributions, which were then plotted. The prediction results point to two potential exploration areas: the southern portion of the Amukpe field and the northern portion of the Efe field. The forecast, we feel, will aid in improving the accuracy of exploration while also saving money during the subsequent exploration stage. based on a map depicting the thickness and porosity distribution of gas sandstone. By adding up the gas volume at each grid point, we can quickly determine the reserves. The new technique estimates 50% larger reserves in the Amukpe field than earlier estimates.

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