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RESERVOIR CHARACTERIZATION USING ARTIFICIAL NEURAL NETWORK IN X FIELD, NIGER DELTA, NIGERIA

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Abstract
An integrated approach to reservoir characterization involving seismic attributes extraction and Artificial Neural Network (ANN) analysis of the reservoirs of X field, onshore, Niger Delta was carried out to assess the effectiveness of ANN as a tool for hydrocarbon reservoir study. ANN is a relatively new technique and imitation of the human brain in its basic form. In this study, it was used in the prediction and classification of reservoir properties and facies from well logs and seismic. Facies classification on logs was executed using an empirical relationship between selected logs such as gamma ray (GR), density (DEN) and resistivity (RES) logs which were cross-plotted against one another to determine data suitability. Facies classification on seismic was employed to predict facies distribution without well control. Two attributes, Root Mean Square (RMS) and Relative Acoustic Impedance (RAI) were selected based on their capability to discriminate lithologies. Facies classification on logs showed correlation between GR and DEN, GR and RES, DEN and RES logs to be 69%, 35% and 36% respectively. These values fell within the acceptable range. Facies classification on seismic revealed 44% correlation between RMS and RAI. Hence, ANN analysis effectively distinguished reservoir sands from non-reservoir sands and accurately identified lithologies penetrated by the wells of the Field. The unsupervised neural network was able to distinguish water and hydrocarbon-bearing sands. This technique had proven to be an effective tool for facies distribution studies and could be employed for generation of leads and prospects for hydrocarbon exploration.
Key words: Root mean square, relative acoustic impedance, neural network, facies and attributes

Introduction

Reservoir characterization is important in the identification of hydrocarbon prospects during exploration phase of a Field (Elkatatny *et al.*, 2018). In present day, an Artificial Neural Network (ANN) is becoming one of the most significant human-based mathematical tools, which can be very helpful in reservoir characterization and formation evaluation (Elkatatny *et al.*, 2018). According to Kukreja *et al.,* (2016), ANN is an imitation of the human brain in its basic form. It can analyze incomplete, obscure and complicated information, and arrives at a conclusion. Human brain is made of cells called neurons which are interconnected to form the neural network or the brain (Kukreja *et al.,* 2016). ANN approach is based on parallel processing employed in function approximation, clustering and pattern recognition purposes Hebbs (1949). In this study, ANN was employed in the prediction and classification of various reservoir properties from the integration of seismic volume and well log signatures. According to Lashin and El Din, (2012), ANN can be used for prediction and classification of facies across seismic volumes due to its computational capability of pattern recognition. According to Sakshi *et al.*, (2014), ANN have its merits and demerits. Some of the advantages include; pattern recognition, recognition of hidden/unknown patterns within large data volumes (e.g. seismic volumes), self-organization to create representation or organization of the training information during learning time and adaptive learning to perform various tasks based on data given for training. One of the disadvantages include lack of specific methodology. Many ANN systems cannot describe how they solve problems. Application of ANN to predict the reservoir characteristics is a new emerging trend (Othman *et al,* 2021).

According to Othman *et al,* (2021), an important advantage of ANN algorithm over the other seismic reservoir characterization is the ability to build non-linear relationships between the well logs and seismic data. Seismic facies classification gives a correct location of pay and non-pay facies allowing for prediction of oil saturation and reservoir connectivity (Corradi *et al.*, 2009). The conventional interpretation of seismic facies is a time-consuming and labour-intensive operation even for an experienced seismic interpreter. This can be more difficult when the data to be interpreted is complex. Due to the knowledge of the pros and cons of facies classification, the role of artificial intelligence as a successful hydrocarbon prediction tool is anticipated to grow (Saggaf *et al.*, 2003). ANN can be employed in unsupervised and supervised multi-attribute analysis for the classification of facies on seismic (Tao *et al.,* 2015). In terms of the network structure, supervised neural networks are feed-forward (flow of information is unidirectional). However, unsupervised neural networks are feed-backward (flow of information is bi directional).

Location of study area and geology

The study area is located within the X- Field, at the distal part of the Northern depo – belt, onshore Niger Delta, Nigeria (Fig.1.0). The five wells (SP1, SP 2, SP 3, SP 4, SP X) were located within the Field as shown in the base map (Fig. 2). The Tertiary Niger Delta basin is located in Southern Nigeria at the continental margin of the Gulf of Guinea between latitudes 3^0 and 6° N and longitudes 5^0 and 8° E (Reijers, 1996) (Fig.1). The basin occupies the Gulf of Guinea continental margin in equatorial West Africa and It ranks among the world's most prolific petroleum producing Tertiary Deltas Selley (1997). The Tertiary Niger Delta is divided into three diachronous lithostratigraphic formations ranging from Eocene to Recent (Short and Stauble, 1967) (Fig. 3). They are referred to as the Akata, Agbada and Benin Formations respectively (Short and Stauble, 1967). The Akata Formation is the oldest formation in the Niger Delta. The approximate range of thickness is from 0-600m. The Agbada Formation overlies the Akata Formation in the Niger Delta. Petroleum is produced in sandstone and unconsolidated sands of the Agbada Formation. It is characterised by alternating sandstones and shales with rock units varying in thickness from 30 m (100 ft) to 4600 m (15,000 ft) (Short and Stauble, 1967). The Benin Formation is the topmost unit, composed of fluviatile gravel and sands. It is described as the coastal plain sands which outcrop at Benin, Onitsha and Owerri province and elsewhere in the Delta area Reyment (1965).

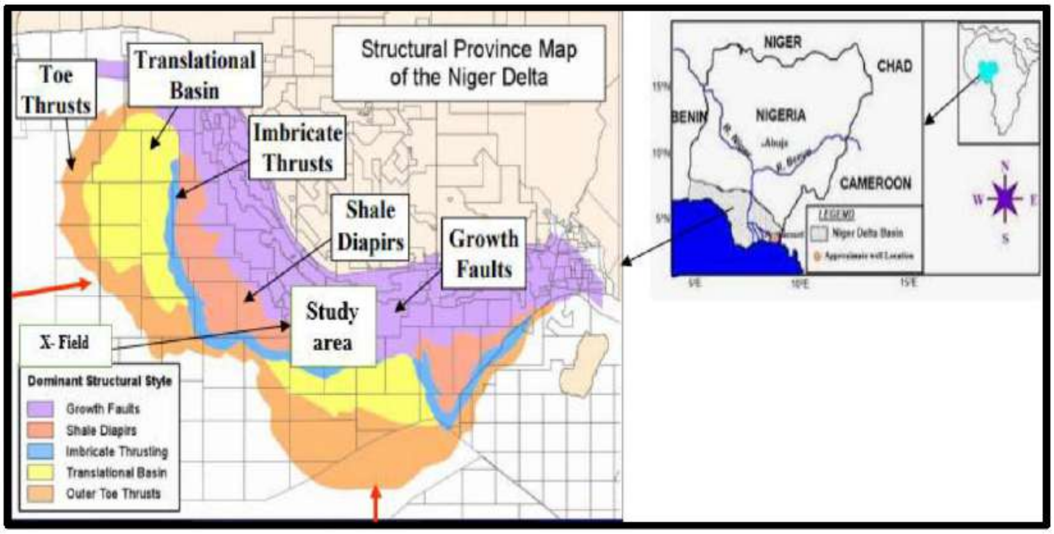

Figure1: Structural province map of the Niger Delta showing the location of study area. Map of Nigeria and Africa inset (Modified from Krueger and Grant, 2006).

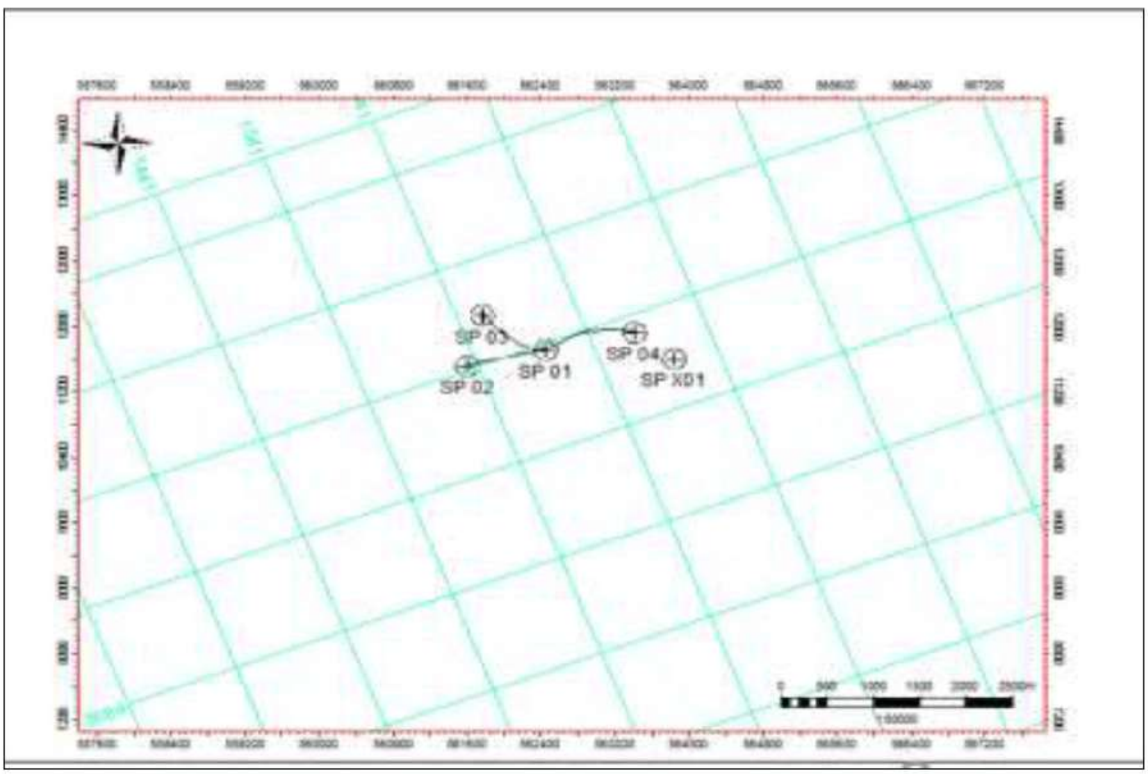

Figure 2: Base map of the study area showing the location of the five wells.

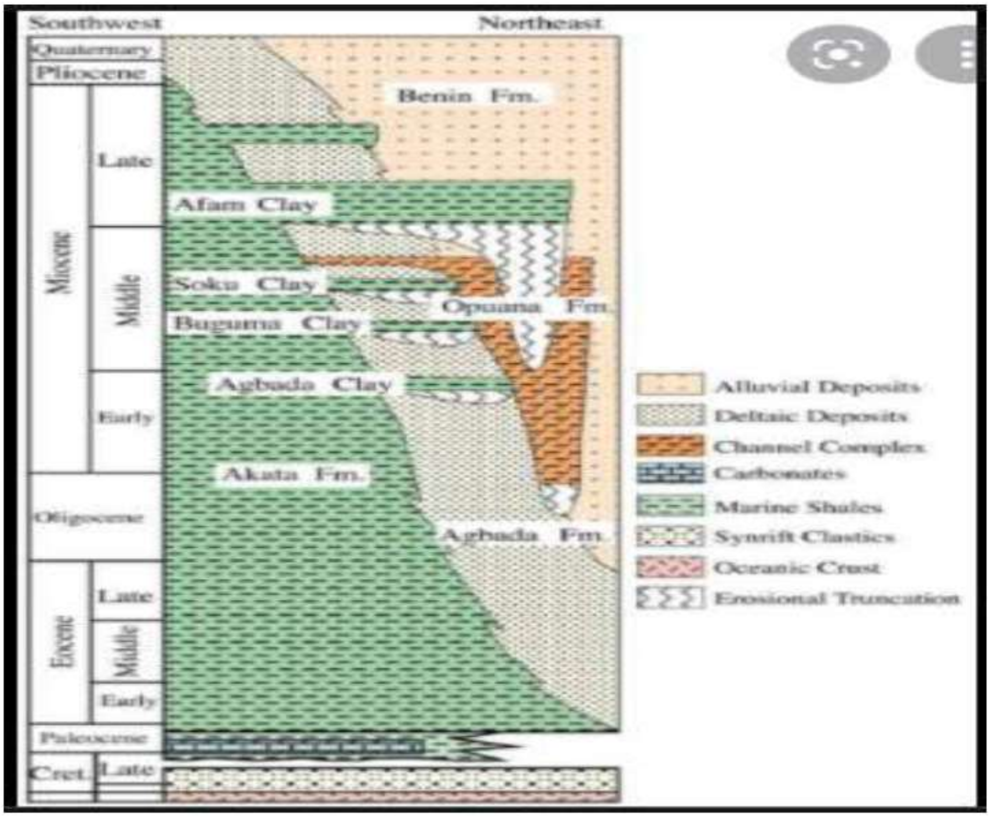

Figure 3: Stratigraphic column showing the three formations of the Niger Delta. Modified from (Shannon and Naylor, 1989) and (Doust and Omatsola, 1990).

Materials and Methods

Materials employed for this study include base map, showing location of the wells, wire-line logs and 3-D seismic, check shot data and Petrel Schlumberger software. The methodology used in this research study is shown in the work flow chart below (Figure 4)

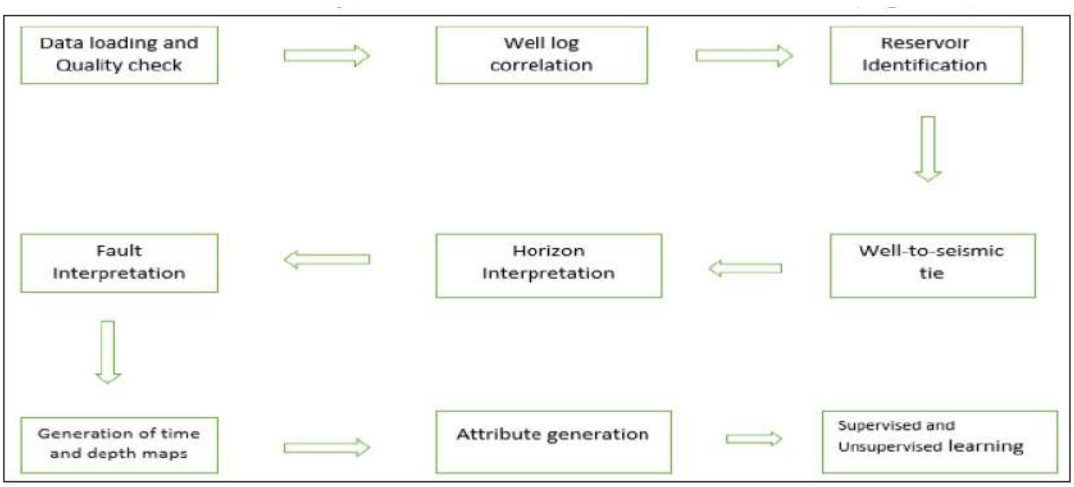

Figure 4: The workflow chart for the study

Data loading and Quality check

The 3-D seismic data was loaded into the Petrel 2014 software for analysis. Quality control of the seismic data was performed by correlating events on the dip lines (inline) and strike lines (cross lines) for continuity. The well logs were also loaded on the software and quality checked.

Well log correlation

The gamma ray (GR) and resistivity logs are good correlation tools in both open and cased holes. In this study, intervals of logs from the five wells were matched for characteristic log responses. The wells were correlated using gamma ray and resistivity logs responses by concept of electric log correlation (Daniel and Richard, 2003).

Reservoir Identification

Reservoirs tops were identified on logs and the combination of both resistivity and gamma ray logs were employed to delineate hydrocarbon bearing sands. Sand units of interest were carefully picked and correlated across the wells to give an idea of the continuity of the reservoirs at different depths across the whole study area. The GR log determines the proportion of shale (Schlumberger (1989). Sand bodies are measured by the deflection to the left due to the low concentration of radioactive minerals while deflection to the right represent shale unit (Schlumberger (1989). Conventionally, GR log is set to a scale of 0-150 API, with cut off point of 65 API units.

Well-to-seismic tie

Well-to-seismic tie was carried out by using check-shot data in order to correlate reflection events visualized on seismic to stratigraphic events on well logs (Alao and Oludare, 2015). The synthetic seismogram used for the well-to-seismic tie was generated from the sonic and density logs with wavelet derived from seismic data.

Horizon Interpretation

Horizon picking was carried out on the seismic section, by picking continuous and strong seismic reflections, which corresponded to the well tops on the synthetic seismogram generated and are usually due to lithological contrast, or presence of an unconformity (Pandey *et al.,*2015). A horizon represents a mappable isochronous geologic time surface. It is associated with continuous and reliable reflection on the sections that appear over a large area.

Fault Interpretation

Faults were mapped based on the following criteria which are reflection termination at fault plane, lateral change in reflection amplitude, overlapping of reflection and abrupt termination of events.

Generation of time and depth maps –

Time and depth structures maps were generated by processing the mapped seismic horizon and employing the convergent interpolation algorithm to make surfaces. The maps revealed the 3-D representation of the mapped surfaces.

Attribute extraction

Attribute generation was carried out on the seismic volume to generate volume attributes which was used for surface attribute extraction (Pandey *et al.,* 2015). This is very important for better visualization of structural and stratigraphic features. Seismic attributes such as Root Mean Square (RMS), structural smoothening, sweetness, cosine of instantaneous phase and variance attributes were extracted.

Neural network analysis (train estimation model)

Artificial Neural Network (ANN) was employed in the prediction and classification of facies on well logs and seismic, surfaces, and faults (Unsupervised ANN). Supervised ANN approach was used to predict petrophysical parameters such as porosity and permeability. It should be noted that all the data selected for training were based on their geological applicability.

Unsupervised Learning (facies classification on seismic)

The 'Train Estimation Model' under 'Utilities' on Petrel software was used for the creation of seismic attributes classification. In this study, an unsupervised estimation model was tested for the prediction and classification of facies using original seismic cube and derived surface attribute extractions. An estimation model was built prior to the computation of the neural network attribute. The input data (attributes) was collected and then neural network attribute was calculated. The selected data for training includes root mean square (RMS) amplitude attribute. Then, a correlation analysis was carried out between the RMS and RAI attributes. The input data such as RMS and RAI were cross-plotted. The cross-plot had a spatial distribution with data points which can be grouped into classes. According to Pandey *et al., (*2015), the attributes analyzed should have a correlation between 0.2 – 0.6. Principal component analysis (PCA) is a linear multivariable approach which was employed in reducing the dimensionality of the input data; hence helping in separating from accessory input data before applying it in the train estimation model (Pandey *et al.,*2015). Reduction of dimensionality reduces the time consumption of the training process and also assisted in reaching a solution with least associated error.

Unsupervised Learning (fault detection on seismic)

The above process was repeated for the detection of faults on the seismic surfaces. The attributes employed for training includes cosine of phase, structural smoothening and variance attributes.

Unsupervised Learning (facies classification on well log)

The training data employed for the classification of facies on logs include gamma ray (GR), density and deep resistivity logs.

Results and Discussion

Well log correlation - Well log correlation result is shown in the Figure 5 below. The log interpretation revealed three hydrocarbon-bearing sands (MT, ST and PT) using GR and resistivity logs responses (Fig 5). These sands showed low GR and high resistivity values.

Horizon interpretation

Horizon mapping was carried out on sand ST to mark off identified reservoir formation tops from well logs on the 3-D seismic data volume after a synthetic seismogram was generated to tie seismic to wells. The horizons of interest were first mapped on the in-lines and checked for consistency on the intercepting crosslines (Figure 6).

Fault interpretation

Interpretation of seismic data was done and associated faults were picked based on abrupt termination of reflection events, dip of events and change in pattern of event (Figure 6).

Generation of time and depth structural map

Time and depth structural maps (Fig. 7 and 8) were generated for the selected reservoirs by processing the mapped seismic horizons and employing the convergent interpolation algorithm to make surfaces. The velocity function calibrated from the check shot was used to generate the depth map of the reservoir top (Fig. 8).

Attribute extraction

Attribute extraction was employed on the seismic volume to generate volume attributes which can be used for surface attribute extraction. This assisted in the visualization of structural and stratigraphic features. In this study, seismic attributes such as RAI, RMS, structural smoothening, sweetness and variance attributes were extracted for the selected reservoir sand (Fig.8).

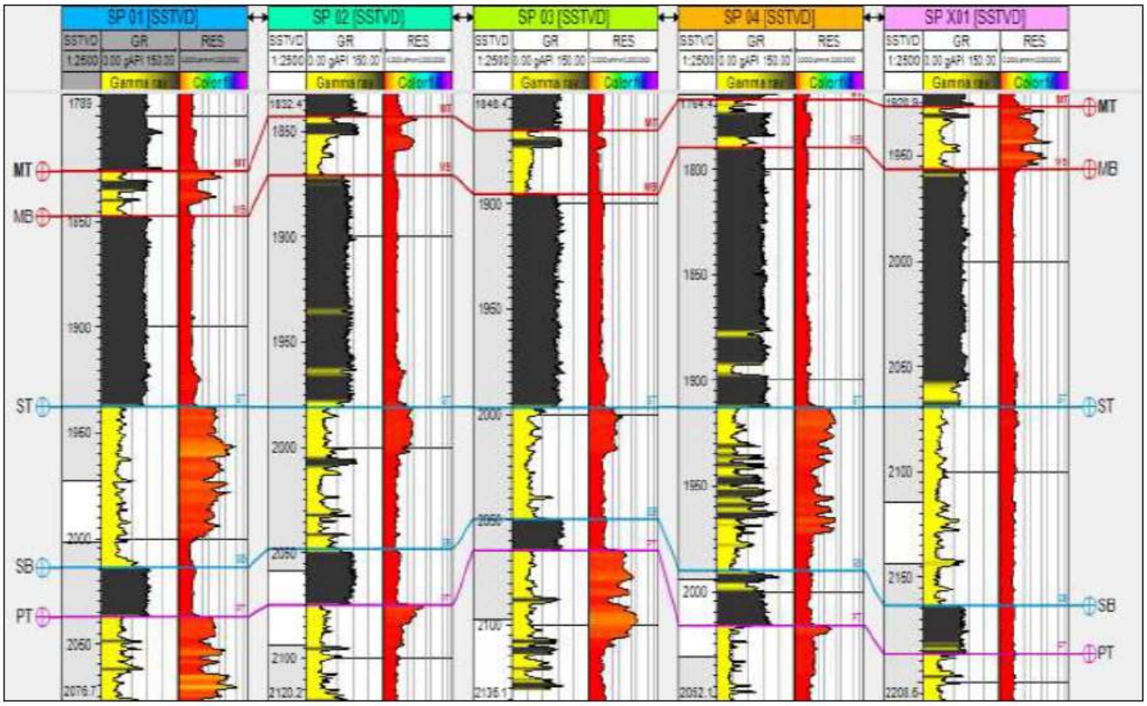

Figure 5: Well log correlation panel showing the reservoir sands of the study area.

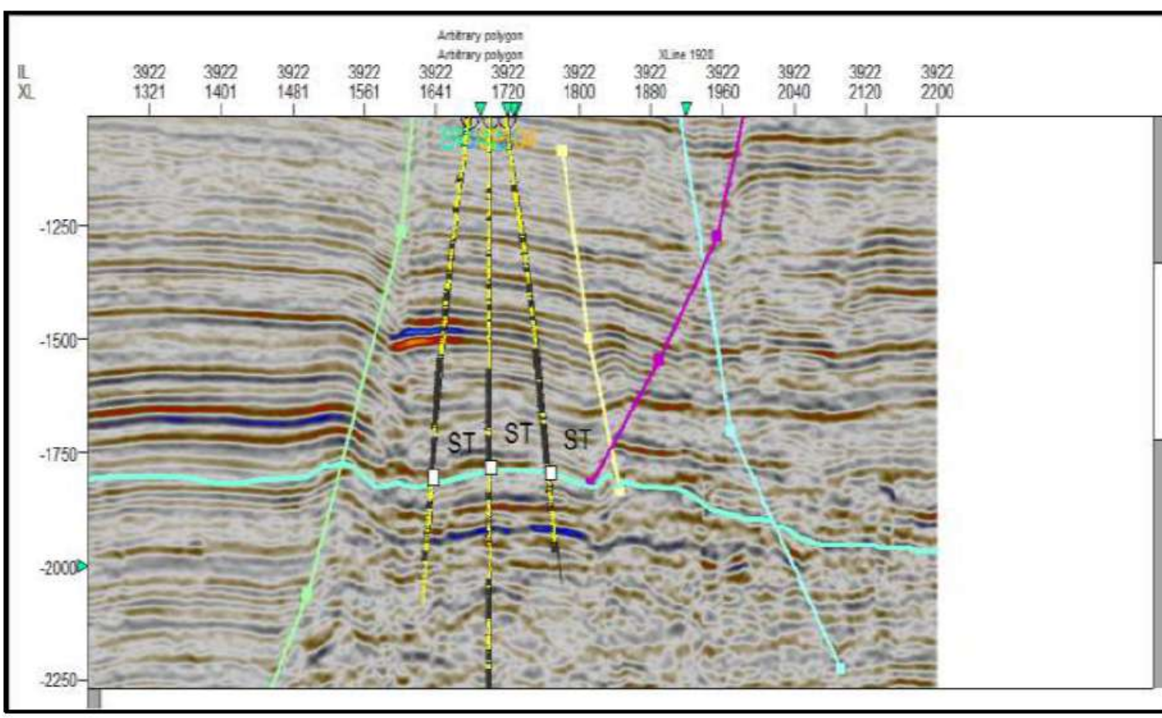

Figure 6: Seismic section of the study area showing both the horizon and fault interpretation

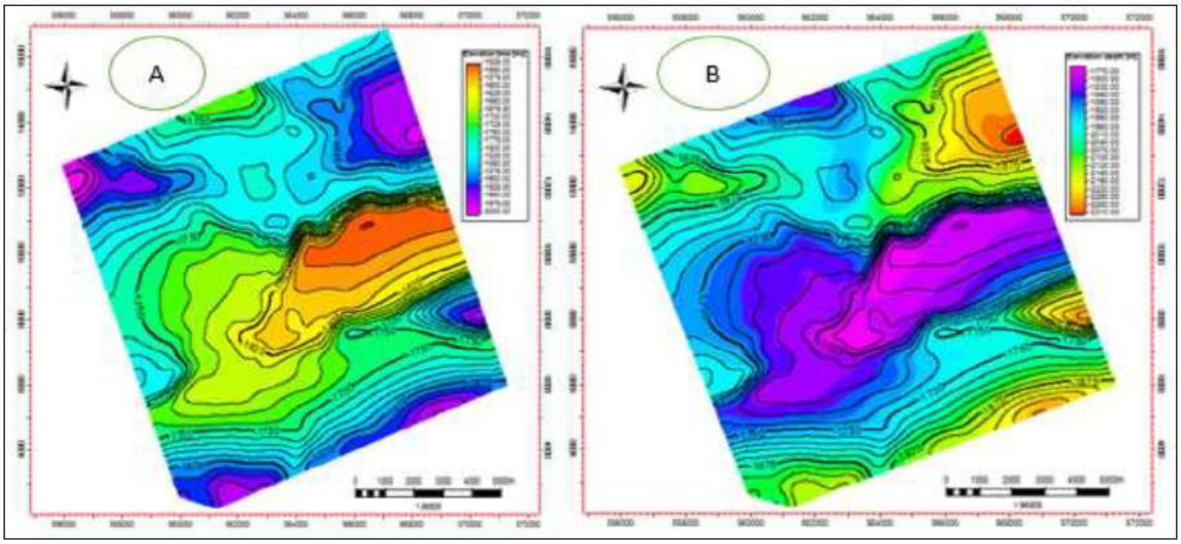

Figure 7: A. Time structural map and B. Depth structural map generated from reservoir sand ST of the study field.

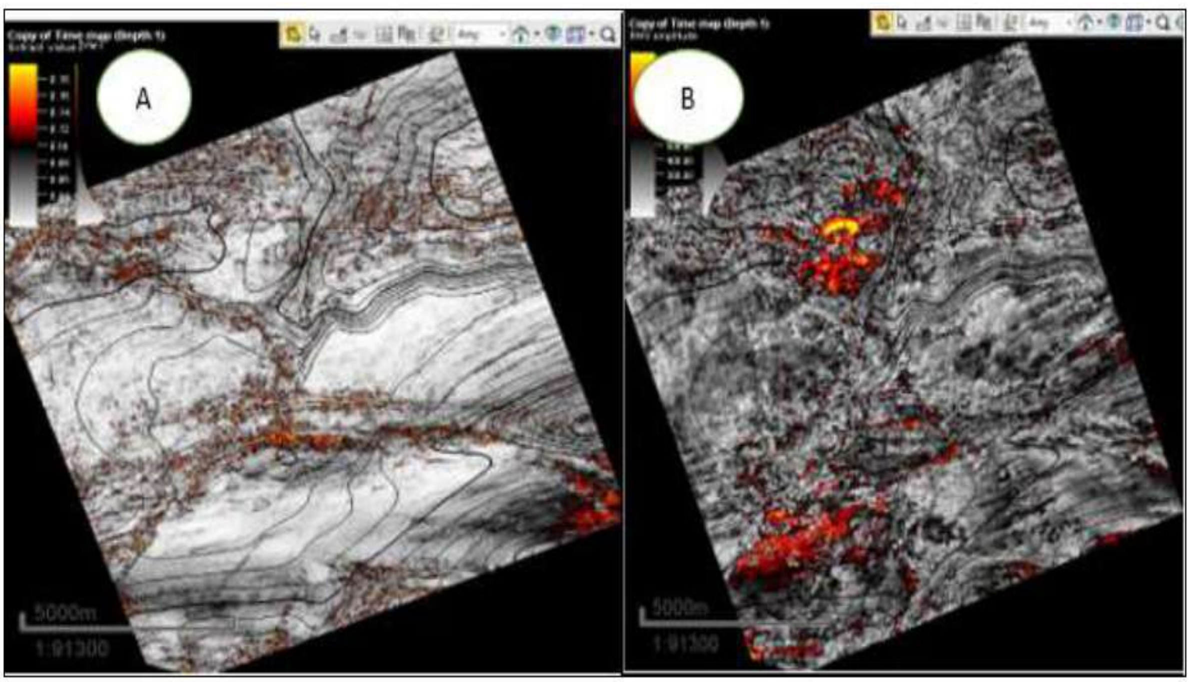

Figure 8: A. Variance attribute and B. RMS attribute extraction for reservoir sand ST of the Field

Facies classification on well logs (Unsupervised ANN)

In order to classify facies on logs, an empirical relationship was established between the selected logs (gamma ray, density and resistivity logs) and employed for training. The logs were cross-plotted against one another to determine suitability of data for training. The results showed correlation between GR and DENS, GR and RES, DENS and RES logs to be 69%, 35% and 36% respectively (Fig. 9). These values were acceptable for training as the correlation values were not too high (e.g. 80-100%) or too low (e.g. 0-20%). Table 1 shows a correlation table of GR, DENS and RES. Principal component analysis was carried out in order to determine the contribution of each data selected for training. The result showed that the resistivity had the highest contribution followed by gamma ray and bulk density. The number of iterations used was 2000, with an error limit of 20%, cross validation of 50%, and three facies classes selected.

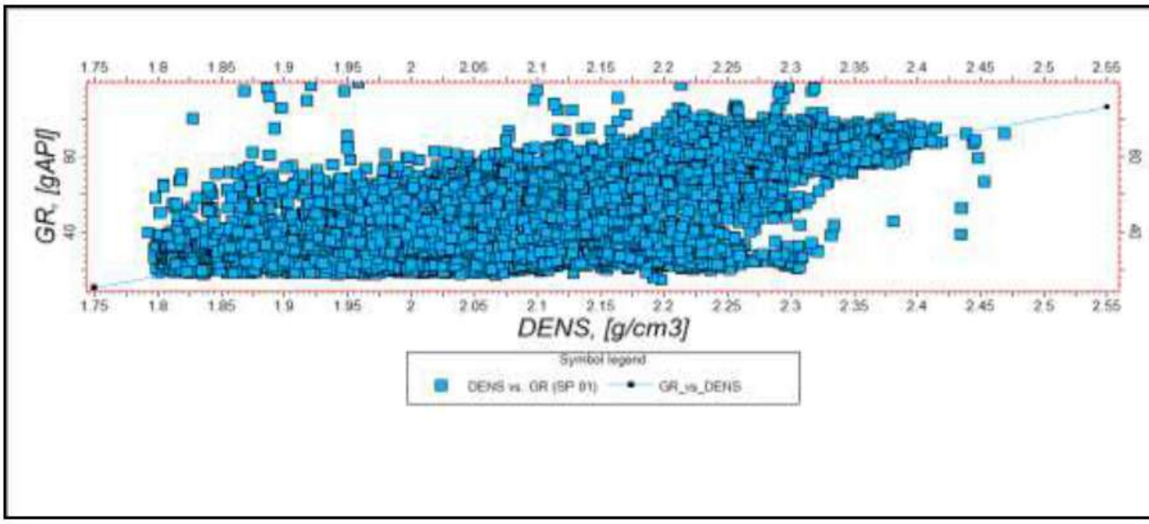

Figure 9: Cross-plot of gamma ray against density for well SP1 of the study field

Table 1: Correlation table showing logs selected for training in facies classification of well SP1; cells in green and light yellow represent most suitable correlation.

Data Input	Bulk density	Gamma ray	Resistivity
Bulk density	1.0000	0.6910	0.3630
Gamma ray	0.6910	1.0000	0.3458
Resistivity	0.3630	0.3458	1.0000
Total	0.7035	0.6985	0.3860

The unsupervised neural network analysis successfully classified the facies penetrated by the SP 1 well based on pattern recognition/clustering. The neural network was able to identify sands and shales. The sand was classified into hydrocarbon bearing and water bearing sands (Fig. 10).

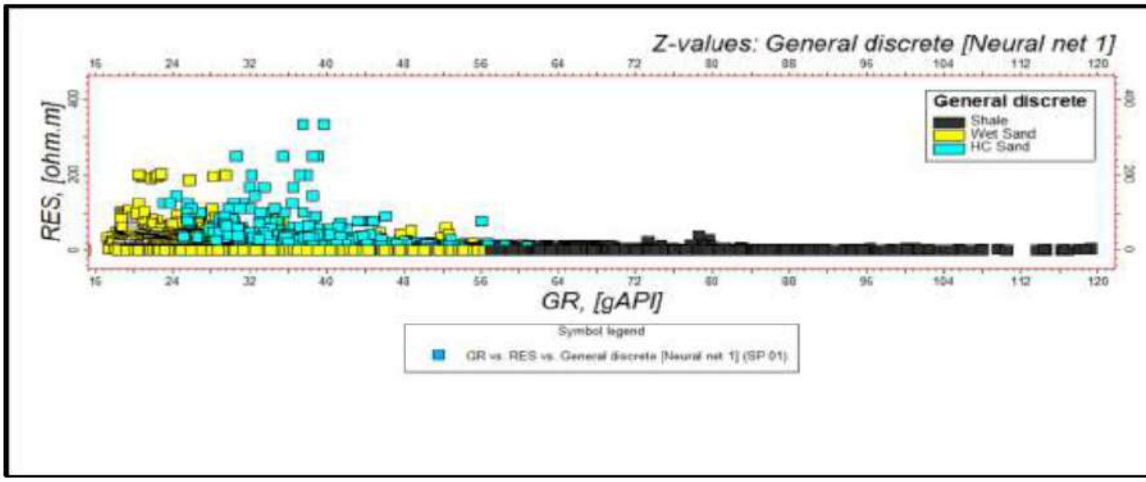

Figure 10: Pattern recognition by clustering in well SP1of the study field (unsupervised learning).

Facies classification on seismic surface

Unsupervised neural network analysis was carried out on a surface (sand ST) to predict facies distribution without well control. Two attributes; RMS and RAI were selected based on their capability to discriminate different lithologies. The RMS amplitude and RAI attributes were cross-plotted to determine data suitability. It showed a correlation coefficient of 44%, which is suitable for training. RAI had the highest contribution for training. The number of iterations used was 3000, with an error limit of 10% and two facies classes selected. Using the attributes selected for training, the neural network successfully classified the lithogies into sand and shale based on pattern recognition (Fig. 11). The neural network facies map shows the facies classification by the neural network into sand and shale (Fig. 12). The validity of the predicted and classified facies was tested by the wells of the study field and there was a very good correspondence between the facies on wells and the predicted facies on seismic (Figure 12). It was also observed that towards the south, there was an increase in sand presence which had a conformance to structure (Fig.12).

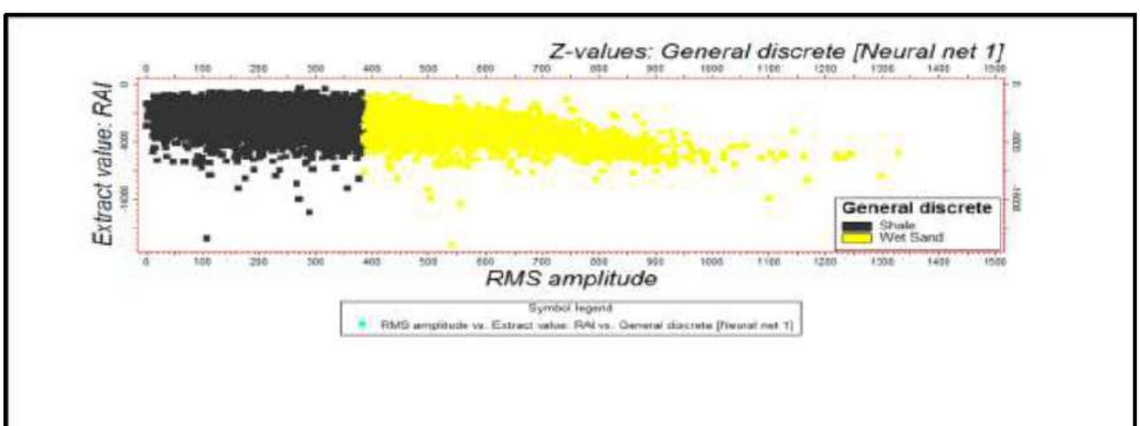

Figure 11: Pattern recognition by clustering for ST surface (Unsupervised learning)

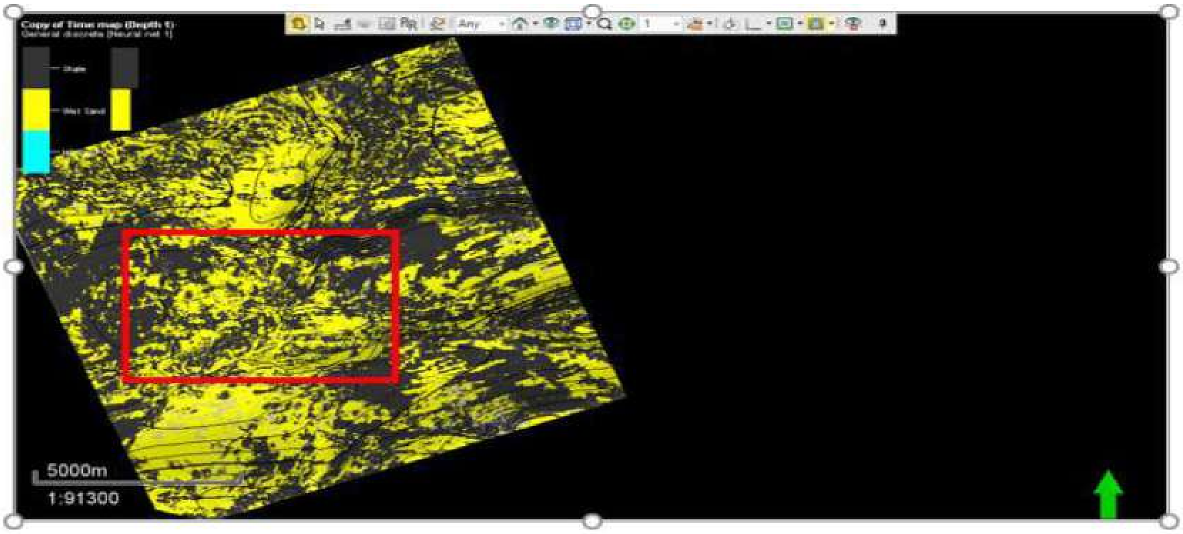

Figure 12: Validity test for facies classification by ANN on surface ST. Area highlighted in red shows undrilled sand which conforms to structure (Yellow is for sand and shale represented by black colour).

Conclusion

An integrated approach to reservoir characterization which involved seismic interpretation, seismic attributes extraction and neural network analysis of the reservoirs of the X field, onshore, Niger Delta was carried out to characterize the field's reservoirs and assess the validity and effectiveness of the ANN as a tool for hydrocarbon reservoir study. Neural network analysis effectively and accurately distinguished reservoir sands from non-reservoir sands (shales). In this study, the unsupervised neural network was able to accurately identified lithologies such as sand and shale penetrated by the wells of the study area. Also, ANN was used to distinguish water and hydrocarbon-bearing sands. Neural network techniques have proven to be a very good tool for seismic facies distribution as shown in the study Field. Hence, it is essentially useful for the generation of leads and prospects in the exploration phase of hydrocarbon prospecting. It was very effective in assessing the hydrocarbon potential of the X field. Artificial neural network technique is an efficient and effective tool in hydrocarbon exploration.

References

Alao, O. A. and Oludare, T. E., 2015. Classification of reservoir sand-facies distribution using multi-attribute probabilistic neural network transform in “Bigola” Field, Niger Delta, Nigeria. Ife Journal of Science vol. 17: 579-589.

Corradi, A., Ruffo, P., Corrao, A. and Visentin, C., 2009. 3-D hydrocarbon migration by percolation technique in an alternative sand-shale environment described by a seismic facies classification volume: Marine and Petroleum Geology, 26, 495–503.

Daniel, J.T. and Richard E.B., (2003): Applied subsurface geological mapping. 2nd ed.pp.60-105.

Doust, H., and Omatsola, E.M., 1990. Niger Delta, In: Divergent/Passive Margins Basins. Edwards, and P.A. Santagrossi (eds), AAPG memoir v. 48, pp. 239-248.

Elkatatny, S., Tariq, Z., Mahmoud, M. and Abdulazeez, A., 2018. New insights into the prediction of heterogeneous carbonate reservoir permeability from well logs using artificial intelligence network. The Natural Computing Applications Forum. DOI:10.1007/s00521-017-2850-x

Hebb., D., 1949. The organization of behavior. Wiley, New York

Krueger, S.W and Grant, N.T., (2006). Evolution of Fault-Related Folds in the Contractional Toe of the Deepwater Niger Delta, AAPG Annual Convention, Houston, Texas, AAPG Datapages, Inc. Online Journal for E&P Goescientists, PP.1-17

Kukreja, H., Bharath, N., Siddesh, C.S. and Kuldeep, S., 2016. An introduction to artificial neural network. Int J Adv Res Innov Ideas Educ, 1, pp.27-30.

Lashin, A. and El Din, S., 2012. Reservoir parameters determination using artificial neural networks: Ras Fanar field, Gulf of Suez, Egypt. Arab J Geosci 6:2789–2806.

Othman, A., Fathy, M. and Mohamed, I.A., 2021. Application of Artificial Neural Network in seismic reservoir characterization: a case study from Offshore Nile Delta. *Earth Sci Inform* 14, 669–676 (2021). https://doi.org/10.1007/s12145-021-00573-x

Pandey, A.K., Negi, A., Bisht, B.S., Chaudhuri, P.K. and Kumar, R., 2015. An Integrated Approach to Delineate Reservoir Facies through Multi-Attributes Analysis in Complex Lithological Environment. SPE-178068-MS.

Reijers, J.A., 1996. Selected Chapters on Geology; Sedimentary Geology and sequence Stratigraphy in Nigeria and a Field Guide, 1996

Reyment, R. A., (1965): Aspect of geology of Nigeria, Ibadan, University of Ibadan Press.

Saggaf, M. and Nafi, T., 2003. Seismic facies classification and identification by competitive neural networks. Earth Resources Laboratory Department of Earth, Atmospheric, and Planetary Sciences Massachusetts Institute of Technology Cambridge, MA. 02139.

Sakshi, K., Surbhi, M. and Rahul, R., 2014. Basics of Artificial Neural Networks. International Journal of Computer Science and Mobile Computing. IJMSC, Vol 3, Issue 9: 745 -751

Schlumberger. 1989. Log Interpretation, Principles and Application. Schlumberger Wireline and Testing: Houston, Texas. pp. 21-89.

Schumberger Petrel* Software: Seismic-to-Simulation, Version 2014.

Selley, R.C., (1997). African basins: Elsevier, pp 1-48

Shannon, P.M. and Naylor, N., 1989. Petroleum Basin Studies. Graham and Trotman Limited: London, UK. 153-169.

Short, K.C., and Stauble, A.J., (1967). Outline of Geology of Niger Delta: AAPG Bulletin, V.51, pp. 761-779

Tao, Z., Vikram, J., Roy, A. and Marfurt, K. J., 2015. A comparison of classification techniques for seismic facies recognition. Special section: Pattern recognition and machine learning 1: SAE 34 – SAE 35