Journal of Basic Physical Research ISSN: 2141-8403 Prints, 2141-8411 Online
Vol.12, No.1 pp. 86 - 98 March., 2024. Available online at www.jbasicphyres-unizik.org

APPLICATION OF SEISMIC INVERSION AND MACHINE LEARNING TECHNIQUES IN RESERVOIR EVALUATION AND OPTIMIZATION SOLUTION IN DIMO FIELD, WESTERN NIGER DELTA, NIGERIA

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Abstract
*Characterisation of litho-facies and fluid types for well planning and development in heterogeneous reservoirs is a very challenging task with no direct solution. However, in this study, we integrate various geophysical tools, namely rock-physic models, seismic inversion and machine learning. The aim among others is to characterise complex reservoir lithogical properties, static and dynamic properties of the reservoir, and to identify bypassed hydrocarbon accumulation channels for further well placement and development. The results of the rock-physics analysis via attribute cross-plotting show the P- impedance and density discriminated four major rock types in the reservoirs namely the sand, the shale, the sandy-shale and the shaly-sand. Sand shows values less than 2.09g/cc - 20000ft/s*g/cc while values greater than 20000ft/s*g/cc are indication shale. The sandy-shale and shaly-sand show density range of 2.09g/cc – 2.28g/cc but with different acoustic impedance ranges. Furthermore, the results of the seismic inversions and density derived probabilistic neural network (PNN) revealed a spatial distribution of reservoir lithofacies and fluid types with an anomalous increase in acoustic impedance and density values around the current well locations. This is probably an indication of brine, or CO_2 gas replacing oil in the reservoirs. The increase in brine saturations esecially around the well locations probably arose from production a related effect, which is a primary indicator of reservoir depletion. Hydrocarbon-charged sands with very low acoustic impedance and density were identified in the northwestern-southeastern trending channel and touted for further exploration consideration. The acoustic impedance attributes and PNN derived density attributes were compared and the results provide an excellent front end but PNN computed density appears more robust, definite and continuous in lithofacies and fluid discriminations.*
Keywords: *Acoustic Impedance, Characterisation, Density, Neural Network, Hydrocarbon*

Introduction

Dimo Field is one of the brown Fields located in the Greater Ughelli Depobelt in Western Niger Delta. The wells have continued to record a huge decline in production despite various enhance mechanisms that were applied to rejuvenate them. Consequently, a repeat survey (4-D seismic data) was completed over the initial 3D seismic data to monitor the changes in the reservoirs for improved well planning and development. Recently, the acceptability of the 4-D seismic technology in reservoir characterisation studies has continued to blaze a new trail in oil and gas industry. The idea of 4-D seismic technology and its applications in reservoir studies first came into limelight about a decade ago when there were noticeable changes in certain acoustic properties of rocks during hydrocarbon production which ultimately, affect the reservoir properties and its overall geometries. Overtime, this has transformed from a mere research idea to a very vital tools in reservoir characterization. Although, its applications in reservoir characterisation and optimisation process is a very challenging task that requires no specific or direct solution. However, in this study, we integrate rock physics models, seismic inversion and nonlinear optimisation problem such as Probabilistic Neural Network (PNN). Among others, the focus is to characterise the reservoir dynamic properties, reservoir fluid saturation sceneries and predict bypassed hydrocarbon channels for further well placement and development. In recent time, rock physics has assumed a leading role in reservoir characterisation studies as it provides the basic relationship between the rock properties, lithology, fluids, and geological depositional environment of the reservoir. Furthermore, rock physics ability to provide the link between the rock properties and the reservoir properties such as water saturation, porosity, permeability, compressibility is the reason why it is widely employed as important tools for efficient interpretation of seismic data. Avseth *et al.*, (2010), Batzle and Wang, (2002) in their separate studies asserted that the model building functionality of the rock physics provides the understanding necessary to optimise imaging and other reservoir characterisation solutions such as seismic inversion. In seismic inversion, seismic reflection data are transformed into a quantitative rock property that is descriptive of the reservoir (Farfour *et al.*, 2015; Nwogbo *et al.*, 2009). The application of seismic inversion methods in reservoir characterisation of high resolution seismic data has been successfully carried in different basins of the world (Duboz, *et al.*, 1998; Pendrel 2006; Sen, 2006; Omofoma and MacBeth, (2015)). Adeyemi *et al.*, (2013), applied seismic inversion method to transform seismic data into a velocity layer model. Salako *et al.*, (2015); Shefa *et al*, (2016) independently applied seismic inversion to produce petrophysical boundaries in the subsurface which make meaningful geological interpretations. Recently, application of seismic inversion method in reservoir characterisation is assuming a new status in reservoir identification, modelling of fluid flow channels and monitoring of reservoir performance. Undoubtedly, this has become a key to finding zones at higher risk of water breakthroughs and bypassed hydrocarbon channels. Furthermore, this production related changes have continued to add more complexity to the reservoir architectures which ultimately limit the characterisation ability of seismic inversion method.

Therefore, we applied a machine learning technique such as Probabilistic Neural Network (PNN) which uses a statistical memory based method that can be supervised or unsupervised. PNN is a classification procedure that roughly mimics the way human brain works, with its non-linear parallel processing approach. The network are often trained with a data and learning algorithm to work and does not need initial guess model as often required in seismic inversion rather it uses a set of one or more parameter measurements called independent variables to predict the value of single dependent variable (Shahraeeni, 2010; Dorrington and Link, 2004; Shahraeeni, 2011). Specifically, the aim is to seismically derive an attributes at every common depth point (CDP) of the seismic data as if we have drilled a well but without physical measurements. The PNN derived attributes would be compared with seismic inversion derived acoustic impedance attributes to determine channel of reservoir quality. The integration is hoped to provide a new insight into distribution of the reservoir dynamic properties, facies architectures and bypassed hydrocarbon zones.

Geologic background

The study area is located in Dimo Field in Greater Ugheli Depobelt in Western parts of Niger Delta (Fig.1) The Niger Delta which is the world's largest Tertiary Delta System ranks among the world's most prolific basin for hydrocarbon production. The rich geologic features of the Niger Delta basin have sustained massive hydrocarbon production for the past 57 years. However, significant numbers of marginal Fields have been documented since the inception of the hydrocarbon exploitations in the basin with few still placed on a recovery programs.

The evolution of the stratigraphy of the Tertiary Niger Delta and underlying Cretaceous strata was first described by Short and Stauble (1967). The lithostratigraphic units were classified into three major subdivisions; an Upper Delta Top Facies; a Middle Delta Front Lithofacies; and a Lower Pro-Delta Lithofacies (Reijers 2011; Weber *et al.*, 1978; Evamy *et al.*, 1978; Okeugo *et al.*, 2018) (Fig.2). The Delta-Top Benin Formation overlies the Delta-Front Agbada Formation and consists of continental sands, gravel while the composition of its subsurface reflects the present day Quaternary land and swamp outcrops. Agbada Formation is major petroleum bearing unit which represents the seat of petroleum explorations and exploitations in Niger Delta. The Akata formation composed mainly of turbidities and continental slope channel fills such as marine shales, with sandy and silty beds often referred to as hydrocarbon source hydrocarbon source kitchen.

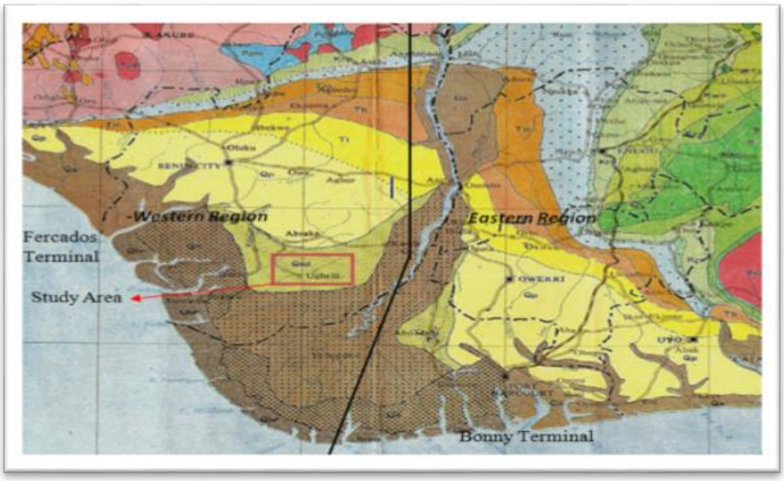


Fig.1. Map of Niger Delta showing location of study area and well locations.

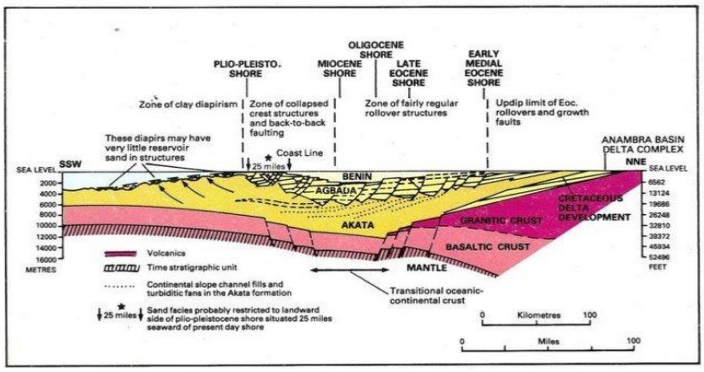


Fig. 2: The classified Lithostratigraphic units of the Niger Delta Basin (Short and Stauble, 1967)

Materials and Methods

The data available for this work include suites of well logs, high resolution 3-D and 4-D post-stack seismic data acquired at different vintages in Dimo Field. The 3-D seismic data set was acquired in the late nineties (1997) and covered about 151kms^2. In July 2010, a repeat survey (4-D seismic data) was completed over the 3D seismic data for reservoir monitoring purpose.

Approach to Rock Physics modelling

Using the transformed equations of E-LOG program, well log attributes were modeled from the available well logs to understand the reservoir condition of the confined space of the boreholes where the physical measurement of the earth properties were taken.

In the available well logs, the S-wave log was not provided but was derived from the P-wave velocity log using Castagna equation (1).

$$Vs = a * Vp + b \qquad 1$$

Where Vs and Vp are S-wave and P-wave velocities in ft/s respectifully.The a and b are the parameters with predicted values of 0.8619 and -3845.14 respectifuly. The equation 1 is valid for brine filled clastic rocks. Although, in hydrocarbon filled zones, the P- wave modulus equation of Gassman may be used to correct for P-wave velocities before it could be utilized for S-wave velocity estimations.

Similarly, porosity log was also derived from the density log using the relations (2).

$$\phi = \frac{\rho ma - \rho obs}{\rho ma - \rho f} \qquad 2$$

where (ρobs) is the observed value of density, ρf is fluid density with constant value of 1.09 gram/cc, ρma is matrix density with constant value of 2.65 gram/cc.

However, with neccesary primary well logs provided, well log attributes such as lamda-Mu-Rho (λ - μ -ρ), P-impedance, Poissons ratio, and velocity ratio were derived from the combination of two or more well logs (Fig 3). The well log attributes were crossplotted and their sensitivities to fluid and lithologies were determined at different well locations.

Approach to Seismic Inversion and Machine learning.

In sesimic inversion, obtaining absolute rock properties is largely dependent on the quality of the low frequency model which basically account for missing low frequency band in seismic data. Using the Strata program, we built the low-frequency model of the base and the monitor data by setting up a typical acoustic impedance inversion process. Using the well logs as the source of amplitude data, the amplitude units, name of the logs was selected and the horizon

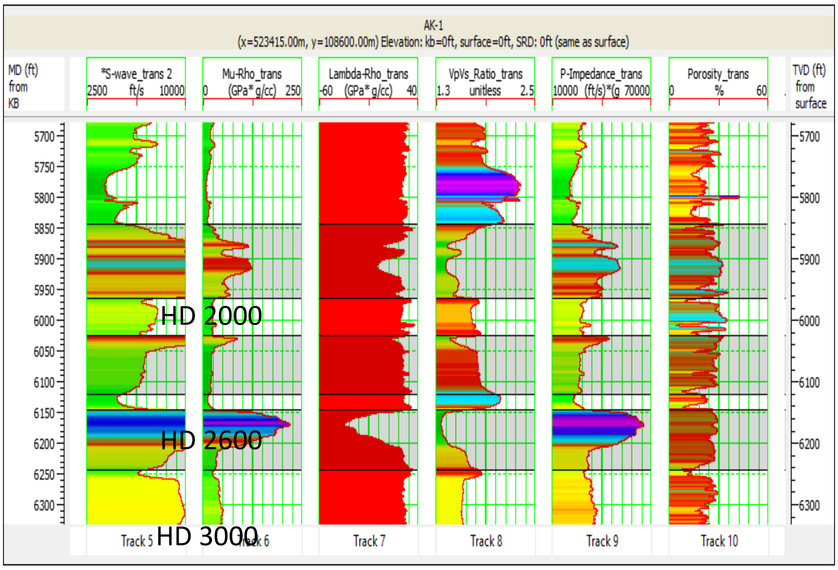


Fig 3: The derived well log attributes

interval to be included in the model was defined. Using model trace filtering options, we apply a smoother on the modelled trace in the output domain with a high cut frequency of 10/15Hz and a low frequency model of P-Impedance was created (Fig.4). However, we created analysis setup for Post Stack inversion and seismic data to be inverted was selected and analysed. We set up model and processing domain range with a sample rate of 8ms where the initial model and wells to be used for inversion were selected. We adjust analysis trace location especially for deviated wells to their corresponding target bottom hole locations. We applied composite extraction method for deviated wells only using neighbour radius of 1 and inversion analysis of Post Stack data was created.

The seismic traces were picked with interpolated logs and matched with low frequency model to ensure good correlation prior to inversion. Here, the initial models with well logs at varying locations were compared with seismic traces at those locations to determine possible misfit. Where there are misfits, we update the model until correlation coefficient value with approximately zero error was obtained. The aim is to create impedance trace that is consistent with wavelet and the input seismic trace at different well locations (Fig.4b). The low frequency models were inverted to derive the impedance profile that matches the modelled trace and the seismic trace in a least square sense using well logs as the constraint. Furthermore, in machine learning using the EMERGE program, the emerge training data such as the inverted seismic data, the raw seismic data, and well logs were imported and calibrated

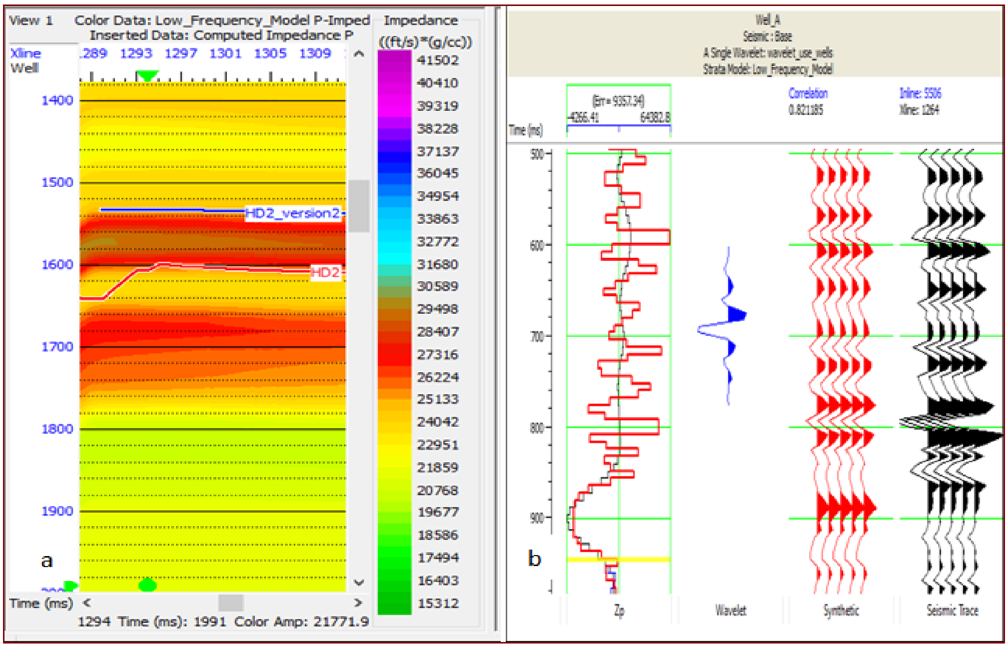


Fig.4a. The low frequency model and (4b) the stratat model showing model log (red), inverted log (blue), single wavelet, synthethic and the seismic traces.

to find their relationships at well locations (Fig.5). The red curve represents the target density log (well derived acoustic impedance), blue curve is the inverted seismic data (seismic derived acoustic impedance at well control) referred to as "external attribute" and the dark curve represent the raw seismic volume (seismic trace at well control). The grey horizontal lines across the curves are the prediction or interval window. The prediction outside this interval may not be added during validation because the program only predicts what it learnt. The density log was converted from depth to time at a sample rate of 4ms as the seismic data. This is very crucial to the process because we are correlating over a time window. However, we established the relationships that exist between the seismic attributes and the well log data at well control (Fig.6). Similarly, we established the relationship between the several seismic attributes and the well log data at well control. The seismic attributes were analysed before training to obtain the most important attributes for log prediction considering their uniqueness. We did this by creating single attribute list which revealed attributes with poor cross correlation co-efficient which was improved by simply applying residual time-shift.

The crossplot of the predicted versus the actual density from the log shows 72% correlation in the reservoir zone (Fig.7).This indicates that the predicted density fairly matched with actual density with prediction error of 0.11%. More also, we carried out multi-attribute analysis which consist of five attributes, derived from the seismic trace and the external attributes using 3 point convolutional operator. Here, a linear combination of weighted attributes was built using attributes that showed best correlation between the original log and the model to estimate the target log. However, the predicted attributes were applied to the seismic data in a process known as validation. The validation process carries all training data and compares each output sample with each training data. The final output is the predicted density rock properties at every common depth point (CDP) of the seismic volume where the density slices were extracted and compared with inverted impedance slices for reservoir evaluation.

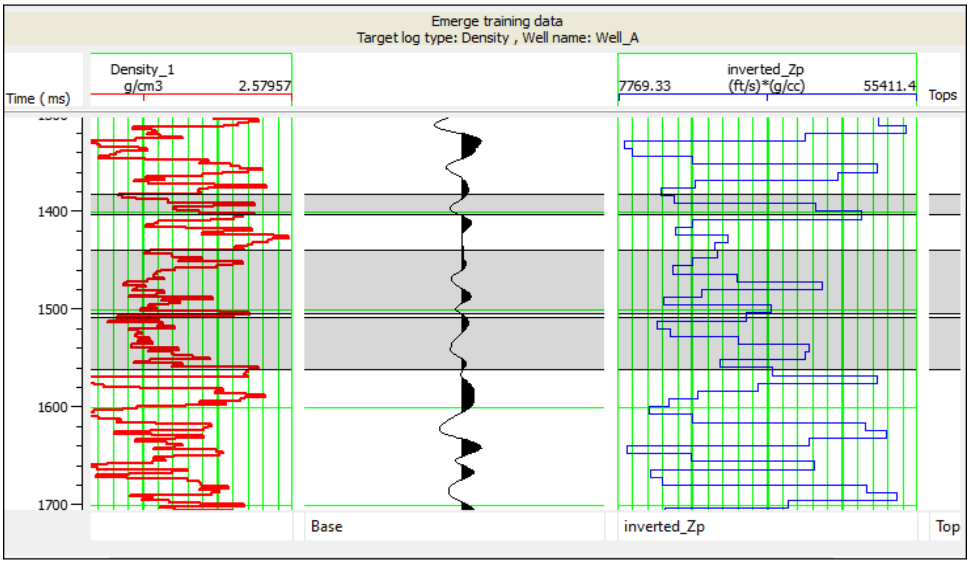


Fig.5: The training data for a single well showing the target density log (red curve), the composite seismic trace from the 3-D volume at the well location (Dark curve) and the composite acoustic impedance from the seismic inversion.

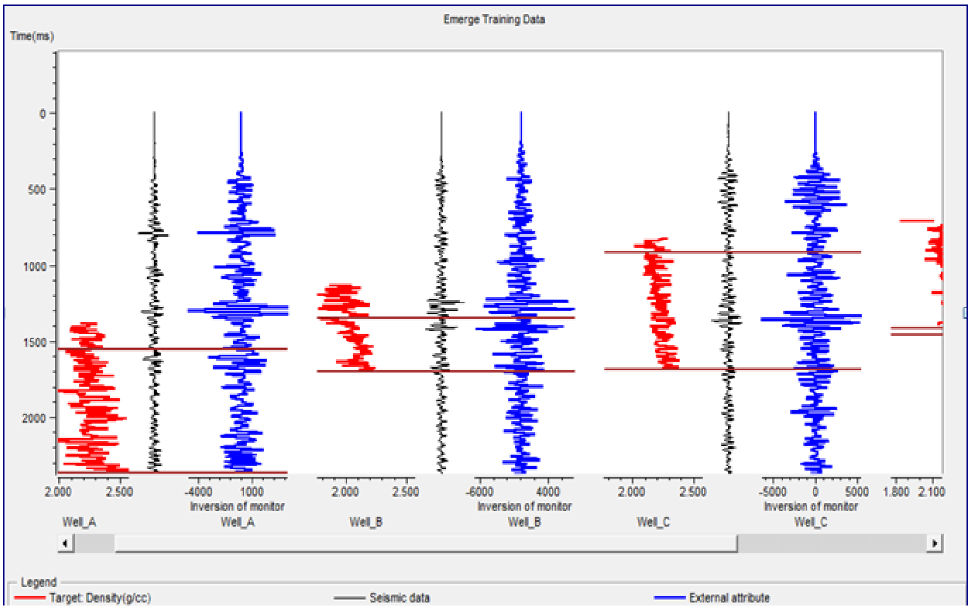


Fig.6: The relationship between the well logs, seismic data, inverted seismic data and prediction intervals at well control

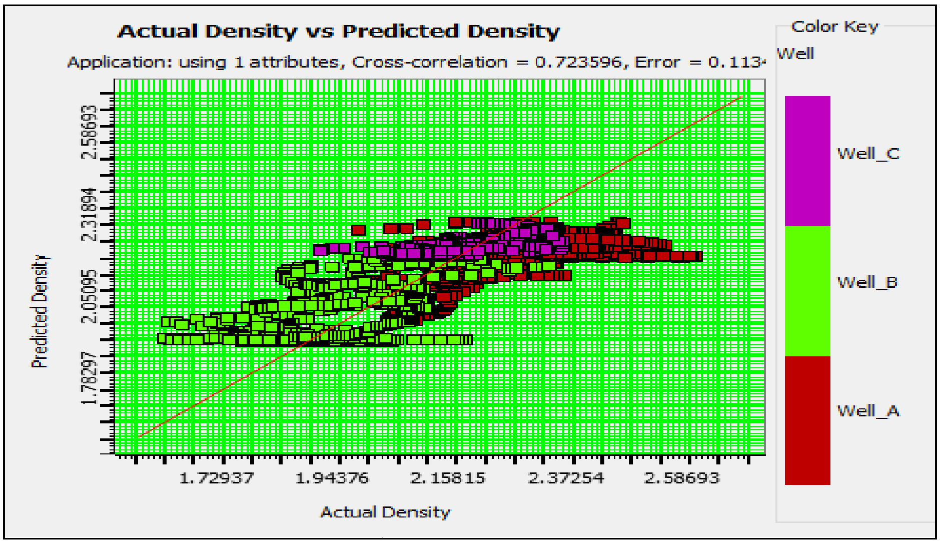


Fig.7. Cross plot between Predicted vs. Actual porosity from Multi Attribute Analysis

Results and Discussions

The cross-plot relations and colour overlays of the computed attributes revealed the litho facies and fluid distributions in the reservoirs with each attribute showing distinctive quality. The crossplot of density and acoustic impedance correlate in unique linear pattern and mapped the hydrocarbons (red), brine (blue) and shale (gray) dominated zones in the reservoirs (Fig.8a-b). Similarly, the crossplot of P-Impedance versus velocity ratio (Fig.9a), Lamdah Rho versus Mu-Rho (Fig.9c) and their colour overlays (Fig.9b & 9d) mapped hydrocarbon, brine and shale dominated zones in the reservoir. Characteristically, hydrocarbon saturated zone shows very low acoustic impedance and density. Here, the density and acoustic impedance lithology cut-off for sand (hydrocarbon saturated zone) is less than 2.09 g/cc and 20000 ft/s*g/cc respectfully. The sandy-shale and shaly-sand showed similar density range of 2.09g/cc – 2.28g/cc but with different acoustic impedance ranges. The density and acoustic impedance values for shale is greater than 2.28 g/cc and 20000 ft/s*g/cc respectfully. The results showed that sand stone has low values of acoustic impedance, density and Lamdah-Rho, which are typical of the hydrocarbon bearing units as indicated in the crossplot relations. Shale shows high acoustic impedance, Lamdah-Rho, velocity ratio and density values. The classification of reservoir lithofacies using crossplot relation of computed attributes is very vital in calibration and prediction of reservoir fluid properties especially at confine well locations. The lateral variation of these reservoir fluid properties were effectively analysed using seismic inversion method which typically revealed the lateral reservoir lithofacies and their distributions (Fig.10).

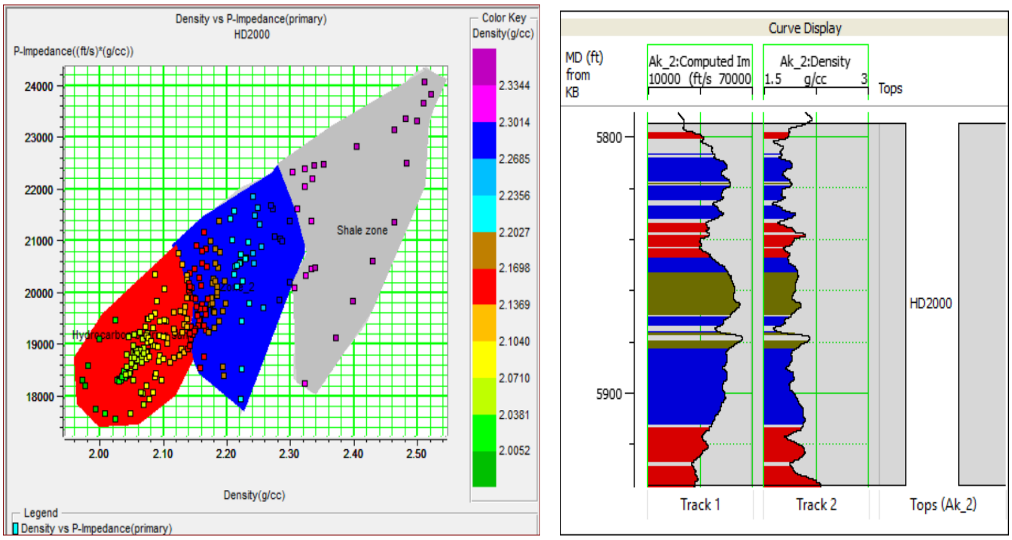


Fig 8a-b: (a-b) Crossplot of density versus P-Impedance and (b) their curve display

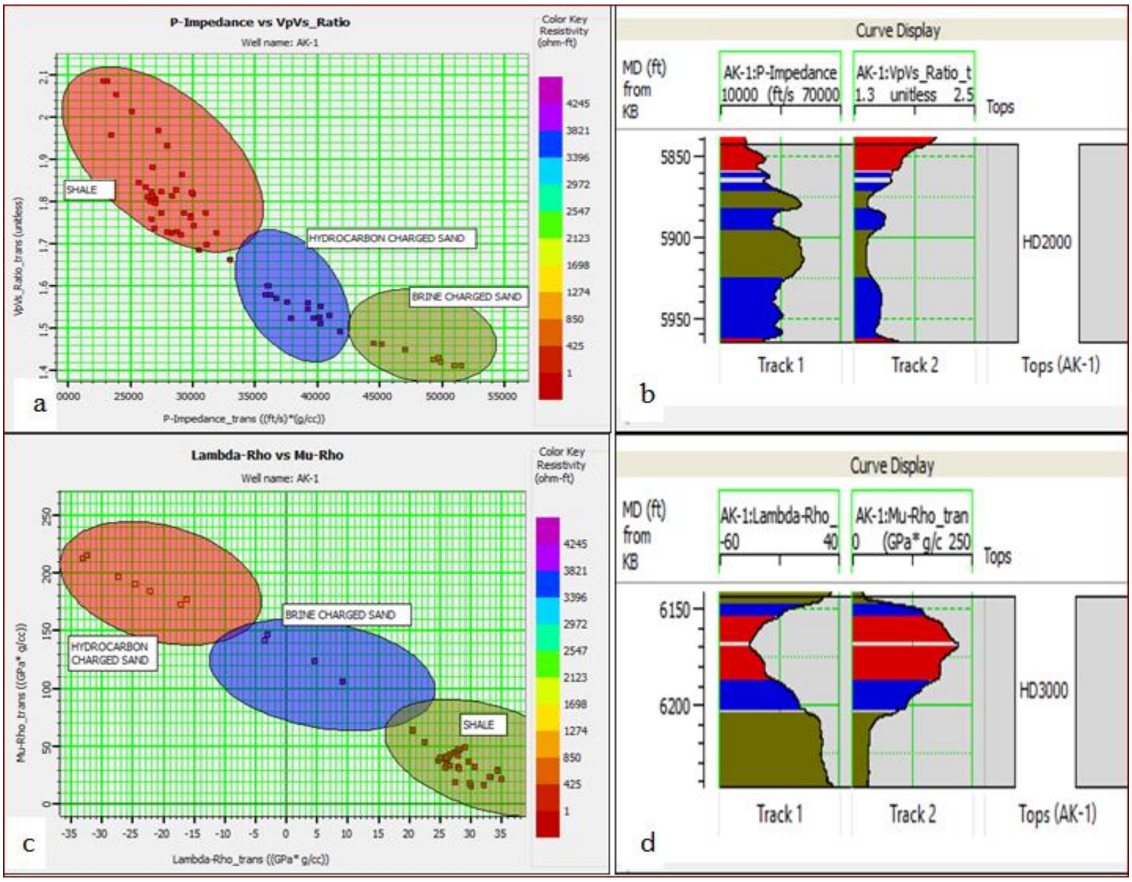


Fig 9a-d: (a-b) Cross-plot of P-Impedance versus Velocity ratio and their curve display at HD2000. (b-c) Cross-plot of Lamdah Rho versus Mu-Rho and their colour overlays at HD300

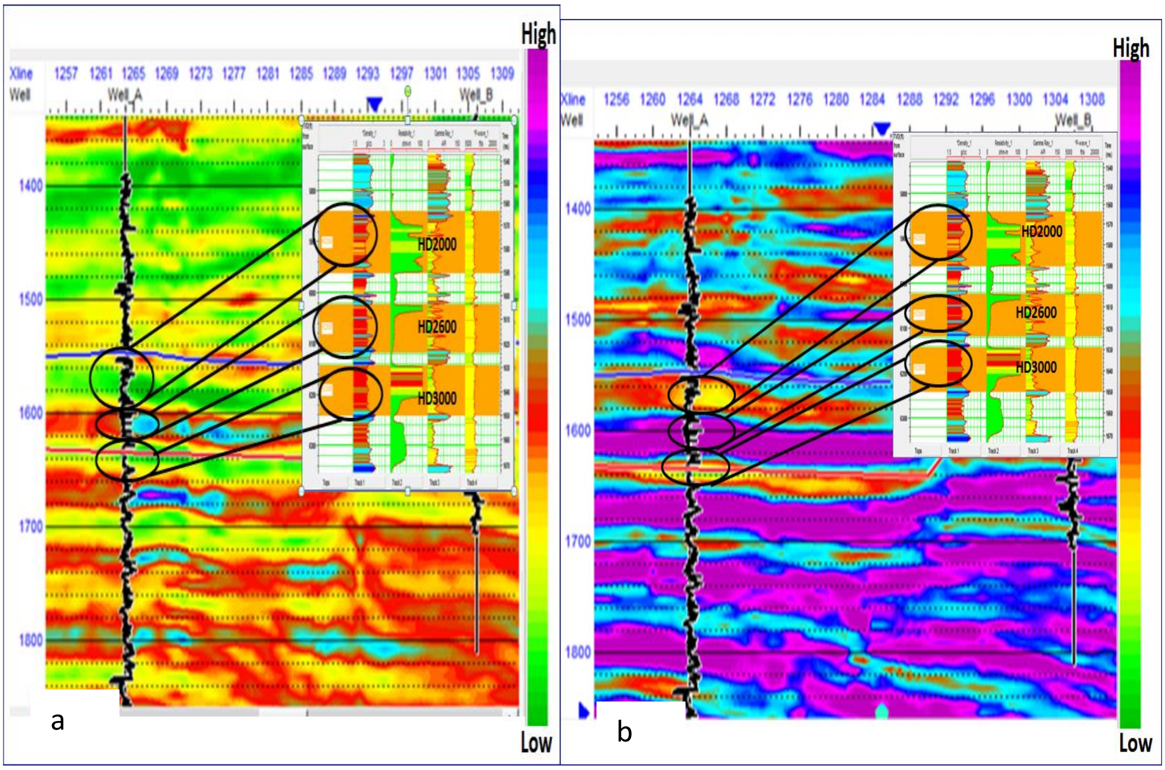


Fig.10a-b. (a) The inverted base and (b) monitor with inserted well logs and horizons

Using the side colour bar, from green to pink indicates the increasing order of acoustic impedance. A very low acoustic impedance values are indication of hydrocarbon charged sand bodies. The shale and brine saturated zones reflect a very high and high acoustic impedance values respectively. The inverted base and the horizons showed significant low acoustic impedance values which are typical of hydrocarbon charged sand. The horizons (inverted monitor) indicate production related effects (anomalous increase in water saturation) which are typical of reservoir depletion as indicated by very high acoustic impedance values. Reservoir water encroachment may also arise from hydrocarbon recovery mechanisms such as water/steam injection, thermal heating, fracking, natural gas re-injections often apply to the depleting reservoirs to recover hydrocarbons. The aim among others is to facilitate the flow of hydrocarbons into the wellbores for easy exploitations. This often increases recovery efficiency by 35% depending on the reservoir lithofacies and its pore throats. Although, it could also affect reservoir quality especially if the water is not properly channelled thus leading to abnormal increase in reservoir water volume, forceful migration of the hydrocarbons to the nearby reservoirs and increase in reservoir pressure as visibly in the inverted monitor data. The positive or increase in acoustic impedance anomalies in HD2000, HD2600 and H3000 reservoirs in the monitor data probably occurred due to water, or CO_2 gas replacing oil in the reservoirs. These reservoir imprints are also evident in density derived Probabilistic Neural Network (PNN) volume (Fig.11).

We compared the instantaneous frequency and density attributes slices of the inverted monitor and PNN volume to determine the responses of the lateral changes in water saturation, fluid flow and bypassed hydrocarbon channels on both seismic volumes.

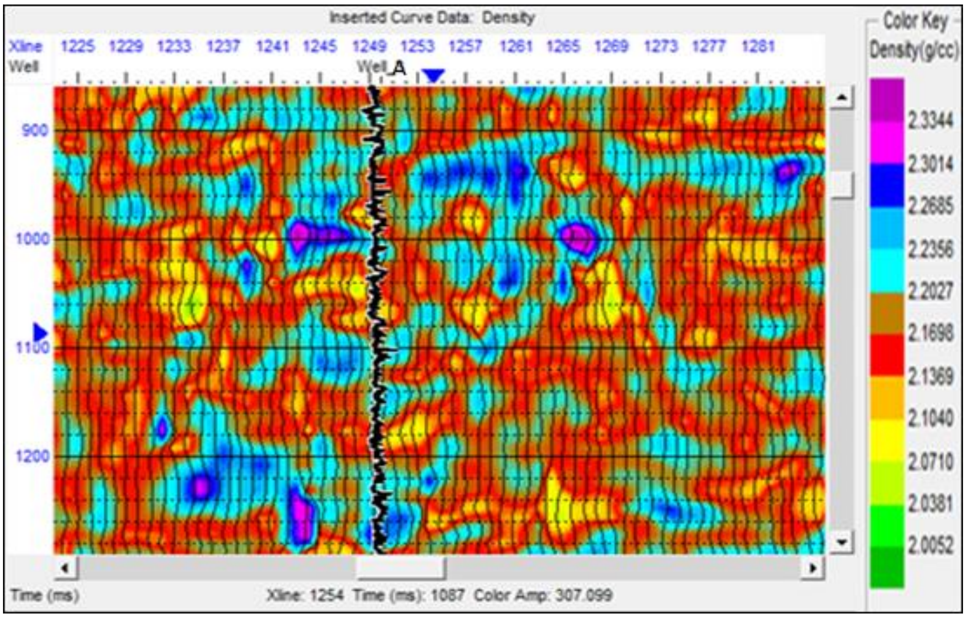


Fig.11: PNN derived seismic volume with inserted density curve

The frequency attribute was computed from the time derivative of the phase through sample by sample measure of frequency which has assumed an effective role in hydrocarbon discrimination and bedding classification (Fig.12a-b). Similarly, the density derived PNN attributes were computed from the PNN seismic volume (Fig.13a-b). Both attribute slices (Instantaneous frequency slices and density derived PNN attribute slices) at HD2000, HD3000 and HD2600 showed relatively high instatneous frequency values especially around the well locations (an indication of production of production related effects). However, each horizon indicates hydrocarbon sand channels with very low acoustic impedance and density values (black enclosures) outside the well locations. Characteristically, acoustic impedance of rocks varies with different factors such as fluid types and their saturation, depth and inter-

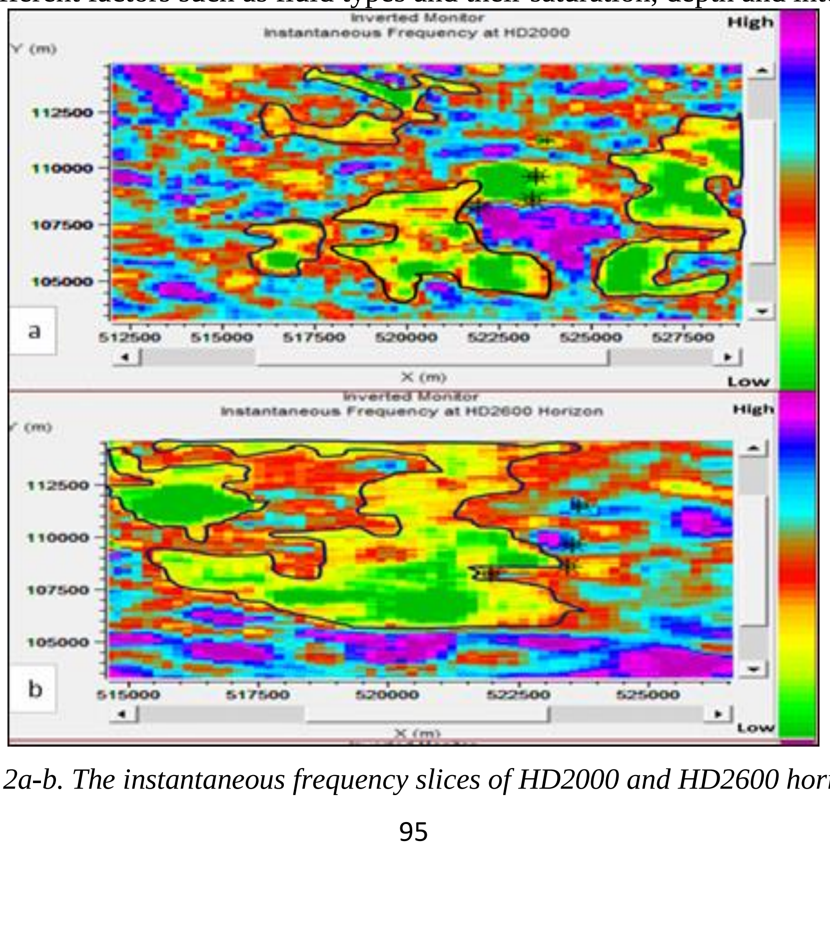


Fig.12a-b. The instantaneous frequency slices of HD2000 and HD2600 horizons

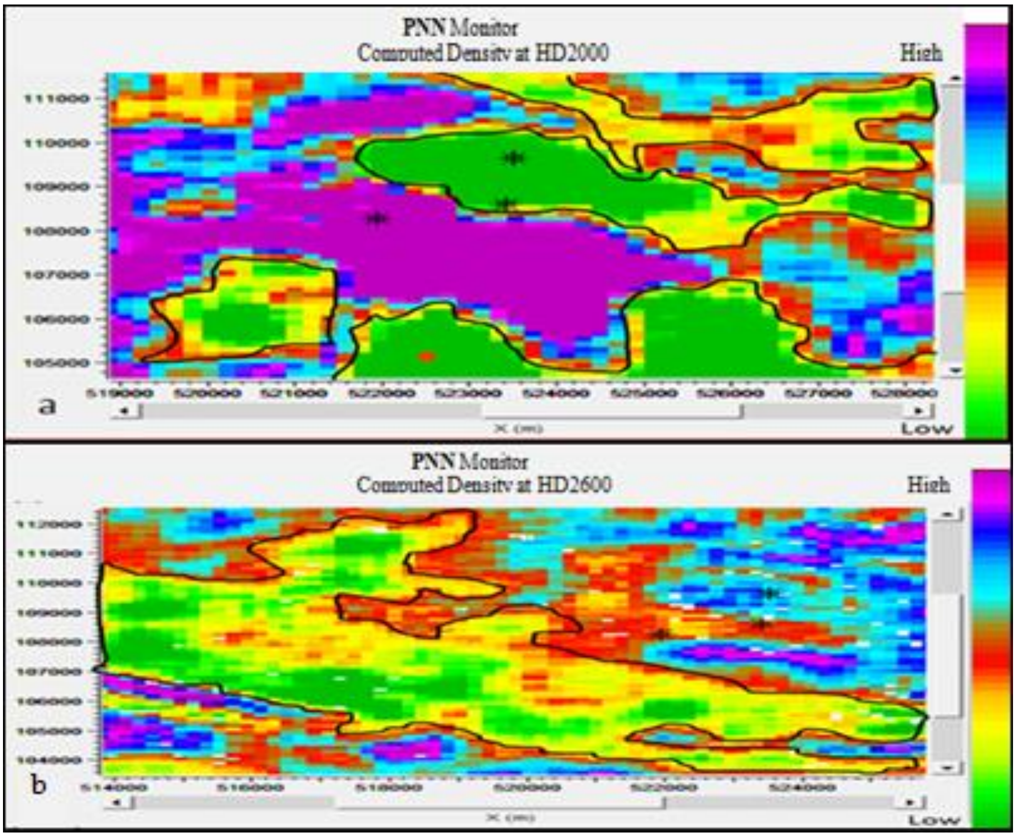
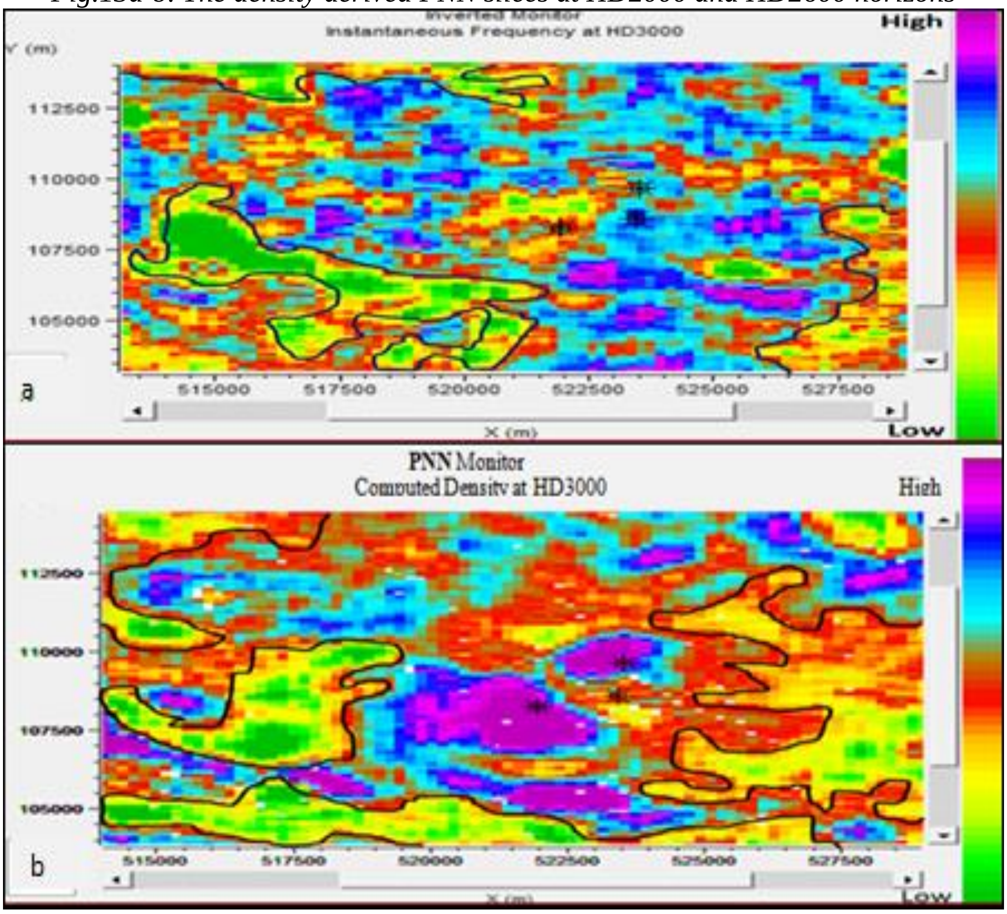


Fig.13a-b. The density derived PNN slices at HD2000 and HD2600 horizons



granular porosity. For instance, in sand dominated zones, lowering of the acoustic impedance values usually occur but that also depends on the fluid content of the sand. In hydrocarbon charged sands, the acoustic impedance values is usually very low but indicate a very high acoustic impedance value in water charged sands as evident around the well locations in each horizon. The PNN derived density attribute slices also reflect the similar trend. However, this may suggest that the high impedance contrasts and density around the well locations in each horizon is an evidence of water encroachment which may also be an indication of reservoir depletion. Furthermore, the computed attributes slices have shown that the present well locations along each horizon may be saturated with brine. The black enclosures out the well locations are the hydrocarbon charged sands which may be suggested as the potential targets for further drilling. Although, concise depositional model need to be developed to validate their structural trapping and its viability. Comparatively, the acoustic impedance derived attributes and PNN computed density attributes slices provide an excellent front end in reservoir production and bypassed hydrocarbon status. For instance, the brine saturated well locations are accompanied with high values of acoustic impedance and PNN computed density but the discriminating strength of the PNN computed density appears more robust as shown in Fig.12band Fig 13b. The well locations are saturated with brine with high acoustic impedance and density. The low values of density and acoustic impedance outside the well locations are the hydrocarbon charged sand which also appears more definite and continuous in PNN computed density slices. In HD2600.Similarly,at HD3000 reservoir, the present well locations are brine saturated. The hydrocarbon charged sand is distributed along the south east and southwest with PNN computed density slices also appearing more robust and continuous.

Conclusion

Seismic Inversion and Machine Learning Techniques have been integrated to characterise the dynamic reservoir behaviour in Dimo Field; an old producing Field located in the western Niger Delta. The study highlighted the effects of fluid flow saturations in the reservoirs, track the production related changes, and identify bypassed hydrocarbons sand zones for further development using different geophysical tools such as rock-physics models, seismic inversion and machine learning. Rock-physics tools provide unique cross-plot relations that were used mapped, calibrate and classify reservoir litho-facies and fluid properties especially at confine well locations. The lateral variations of these reservoir fluid properties were analysed using seismic inversion and machine learning techniques. The inverted seismic data and density derived attributes of PNN seismic volumes revealed varying production related effects in the reservoirs. The well location and its environs indicate an anomalous increase in water saturation which are typical of reservoir depletion and indicated by very high acoustic impedance values. Furthermore, we derived bypassed hydrocarbon channels and migration trend using instantaneous frequency and density derived PNN slices computed from the inverted and PNN seismic volumes respectively. We compared their lithofacies and fluid properties discrimination strength, both provide an excellent front end but PNN computed density attribute slices appeared more robust as and continuous in lithofacies and fluid properties discriminations.

Acknowledgements

The authors acknowledged the Shell Petroleum Development Company, Warri, Nigeria for providing the dataset used for this study. Our sincere gratitude also goes to the staff of Geophysics workstation for their kind attention during the analysis of this data.

Data Availability Statement

Restrictions apply to the availability of the data used in this article.

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