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ENHANCING RESERVOIR CHARACTERIZATION USING DEEP LEARNING AIDED MODEL-BASED INVERSION: A CASE STUDY OF DATA FROM THE COASTAL SWAMP ZONE IN THE NIGER DELTA

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ABSTRACT
Seismic Reservoir Characterization is a pivotal element in seismic data interpretation. This study describes a successful utilization of model-based seismic inversion methodology coupled with a Probabilistic Neural Network for the identification of hydrocarbon reservoir zones within post-stack seismic data. The paper unfolds in two segments. Initially, Acoustic Impedance (AI) volume is extrapolated from seismic datasets via the application of the model-based inversion algorithm in the time domain. The strong correlation coefficient of 0.988 between synthetic and seismic data underscores the effectiveness of model-based inversion. Subsequently, a Probabilistic Neural Network (PNN) undergoes training, validation, and testing utilizing estimated porosity data at well locations, serving as internal attributes, and the outcomes from model-based inversion as external attributes. The trained Probabilistic Neural Network is then deployed across the seismic volume to delineate a three-dimensional map in total porosity. A notable high value of total porosity, ranging from 16 to 30%, observed within horizons A and B, indicates a substantial volume of void spaces within the rock formation. Therefore, the presence of such elevated porosity values in horizons A and B signifies the existence of a promising reservoir with ample capacity for fluid storage and migration, which is scientifically significant for hydrocarbon exploration and production. The findings from this study underscore the potential of merging model-based inversion and PNN for effective estimation of reservoir properties, particularly in scenarios where the relationship between porosity and acoustic impedance exhibits non-linear characteristics

KEYWORDS: Niger Delta, porosity, deep learning, Probabilistic Neural Network, Model Based Inversion, Acoustic impedance

INTRODUCTION
A reservoir is defined as an underground rock formation with adequate porosity and permeability to store and transmit fluids. It plays a crucial role in the petroleum system, making high-resolution characterization a primary focus of geophysical surveys. Currently, most seismic methods used for reservoir characterization rely on interpretation-based approaches (Partyka *et al*., 1999; Zhang *et al*., 2019). Seismic attributes, derived from stacked images or pre-stack seismic data, are often translated into reservoir-related properties such as fluid identification or facies. While extracting seismic attributes from migrated images involves solvable linear inversion, achieving true-amplitude imaging poses practical challenges. Stochastic reservoir characterization, which aims to align with pre-stack seismic data, necessitates dimensionality reduction of seismic attributes to ensure computationally feasible processes (Narayan *et al*., 2023).

The application of seismic inversion techniques has seen a notable rise over the past two decades due to their efficacy in hydrocarbon detection. By combining seismic inversion with log data, it becomes possible to extract critical petrophysical properties of the subsurface, including porosity, volume of shale, acoustic impedance, elastic impedance, and density. Through seismic inversion, seismic data is transformed into a velocity layer model, facilitating the delineation of petrophysical boundaries within the subsurface and enabling meaningful geological interpretations (Liu *et al.*, 2022). Parameters such as P-impedance, S-impedance, density, and porosity are derived from these inversion techniques, thereby providing valuable insights into the properties of the rock formations constituting the subsurface (Smith *et al*., 2023). A neural network is a program that roughly mimics the way the human brain works, with its nonlinear, parallel processing approach. These networks must be "trained" with data and a learning algorithm to work. These networks are sometimes referred to as "artificial neural networks", or ANN (Hampson *et al*, 2001). The advantage of such a network is that:

i. It can predict other logs besides impedance.
ii. It can use other attributes besides amplitude and time.
iii. It does not need a forward model. No need of an initial guess.
iv. It does not require a determined seismic wavelet. 5. It can use cross-validation.

The two main types of problems that a neural network can solve are the classification problem and the prediction problem. In the classification problem, the input dataset is divided into a series of classes, such as sand, shale and carbonate, or gas, wet and oil, etc. In the prediction problem, a parameter of interest is predicted from a number of input values (Soubotcheva and Stewart, 2004). As an input for designing a PNN model, a sample set obtained from the well logs is split into training, validation and test subsets. The training process is carried out until at least one of the following conditions is met: (i) a minimization of a MSE goal is achieved; (ii) occurrence of three consecutive non-improvements in the MSE for the validation subset (early-stopping); or (iii) a maximum number of iterations are completed (Hampson *et al*, 2001). The test subset is used only to estimate the prediction power of the PNN by performing a blind test and it is not used for building the NN model.

Probabilistic Neural Network (PNN) is a type of artificial neural network that has found applications in various fields, including reservoir studies in the oil and gas industry. In reservoir studies, PNNs are used for tasks such as reservoir characterization, fluid property prediction, well log interpretation, and production forecasting. PNNs can be employed to classify reservoir lithofacies based on well logs and seismic attributes. By training the network on labeled data representing different lithofacies, the PNN can learn the complex relationships between input features and lithofacies classes. Once trained, it can accurately classify unlabeled data, aiding in the characterization of reservoir properties such as porosity, permeability, and lithology.

In the context of the present study, the initial step involves conducting model-based inversion on a single trace, which is subsequently compared with the original impedance. The correlation coefficient is then calculated, and if it exceeds 0.7, it is considered indicative of a strong correlation, prompting the inversion of the entire seismic volume to compute the elastic parameters (Maurya and Singh, 2015). In the subsequent part of the study, porosity is predicted using Probabilistic Neural Network techniques. The findings derived from these methodologies are thoroughly discussed.

Location and Geology of the Study Area

The study was carried out in the Niger Delta basin. Fig. 1 is a cross-section of the Niger Delta, showing its stratigraphic composition. The delta hosts a substantial accumulation of sediment and sedimentary rock, featuring three distinct siliciclastic units. The foundational layer, known as the Akata Formation, primarily consists of marine shale deposited during the Late Cretaceous to Paleocene period. This formation serves as the base of the delta and exhibits variations in thickness throughout the region. The sedimentary layers within the Niger Delta exhibit significant variations in thickness and composition. The Akata Formation, positioned at the base, ranges from approximately 2,000 meters at the furthest extent of the delta to a substantial 7,000 meters beneath the continental shelf (Doust and Omatsola, 1990). Overlying the Akata Formation, the Agbada Formation, more than 3,500 meters thick, consists of alternating layers of sand or sandstone and shale, spanning from the Eocene to the Pliocene era. At the topmost layer lies the Benin Formation, comprising continental sand deposits from the Late Eocene to the Holocene, including alluvial and coastal plain deposits reaching up to 2,000 meters in thickness (Avbovbo, 1978).

The structural dynamics of the Niger Delta are predominantly shaped by growth faults, originating from the rapid accumulation of sedimentary material atop the mobile and under-compacted Akata shales. These growth faults serve as the primary structural features, evident across the delta, as depicted in Fig. 1. Additionally, the thrusting at the delta front, lateral flow, and extrusion of the Akata shales during growth faulting contribute to the formation of diapiric structures along the continental slope of the Niger Delta (Doust and Omatsola, 1990).

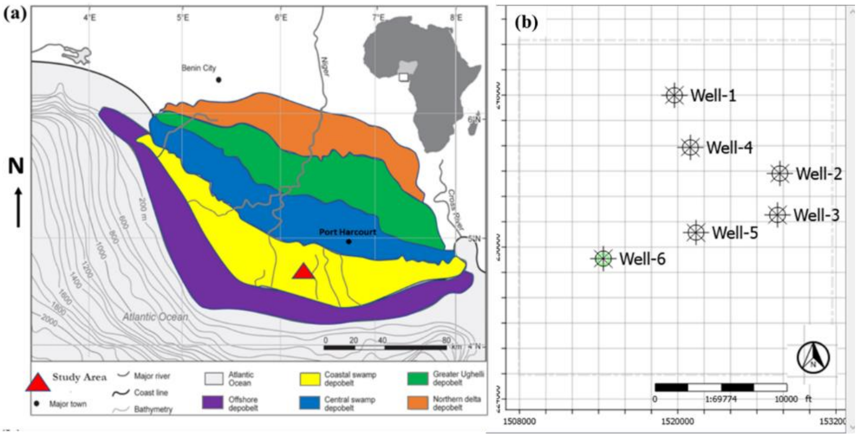

Fig. 1**:** (a) Depositional Belt map of the Niger Delta Basin (after Lucas and Omodolor, 2018). (b) The Basemap of the Wells in the Field.

MATERIALS AND METHODS

Data Sets

The field is located in the Coastal Swamp Depositional Belt (CSDB) of Niger Delta. The data include full offset stack seismic data, quality checked petrophysical wireline logs from existing wells that penetrate the given hydrocarbon discoveries, well checkshots data and other well information which includes well headers, deviation data, well tops, rig floor elevation. \

Model Based Inversion

The Model Based Inversion (MBI) is a type of post stack inversion to compute acoustic impedance from the seismic datasets. The model-based inversion technique is also known as blocky inversion. This method is based on the convolutional theory which states that the seismic trace can be generated from the convolution of wavelet with the reflectivity function. The seismic trace is however noisy due to many factors that influences the data from instrument, multiples to cultural noise.

*Seismic trace = Wavelet * Reflectivity + Noise* (1)

If the noise in the data is uncorrelated with the seismic signal, the trace can be solved for Earth Reflectivity function. This is a non-linear equation which can be solved iteratively (Buxton, 2000) as follows:

$$Z = V * \rho \tag{2}$$

$$r_1 = \left(Z_i + 1 - Z_i\right) / \left(Z_i + 1 + Z_i\right) \tag{3}$$

and

$$AI_N = AI_1 \exp\left(2\sum_{i=2}^{N} r_1\right) \tag{4}$$

These equations are used in practice for recursive inversion with the aim of transforming reflectivity function into acoustic impedance (1). AI_1 is the acoustic impedance of the first (top) layer and AI_N is the Nth layer acoustic impedance. r_i is the reflection coefficient of the ith layer.

An initial low-frequency model for AI is required to perform the inversion which is estimated from well log data. This model provides the low- and high-frequency components missing from the seismic datasets, and also helps reduce the non-uniqueness of the solution. The processing steps of the model-based inversion used in this paper are as follows:

i. Calculate the acoustic impedance at well locations using the well log data.
ii. Pick horizons in the seismic section to control the interpolation and to provide structural information for model between the wells in the area.
iii. Use interpolation along the picked seismic horizons and between the well locations to obtain the initial acoustic impedance model.
iv. Block the initial impedance using some selected block size.
v. Extract statistical wavelet from seismic section.
vi. Convolve the wavelet with the Earth Reflectivity to obtain synthetic seismic trace. This synthetic trace is different from the observed seismic trace.
vii. Next, the Least Squares optimization is performed for minimizing the difference between the real and modeled reflectivity section. This is achieved by analyzing the misfit between the synthetic trace and the real trace and modifying the block size and the amplitude to reduce the error.
viii. Repeat step vii until the lowest misfit between real seismic and synthetic trace is achieved.

Probabilistic Neural Network

Probabilistic Neural Network analysis is performed to estimate the porosity variation in seismic section. The Emerge module in HRS 10.3.2 software was used for this purpose. A well log property can also be computed using attributes of the seismic data on Emerge. That property may be any measured log type such as velocity or porosity, or it may even be a derived lithologic attribute, such as volume of shale (Soubotcheva and Stewart, 2004). The seismic attributes can be calculated internally, or can be used as external attributes. The steps for PNN are as follows:

i. Examine the log and seismic data at well locations to determine which set of attributes is appropriate.
ii. Derive a relationship using Neural Networks.
iii. Apply the derived relationship to 3-D seismic volume to create a volume of the desired log property.

RESULTS AND DISCUSSION

Acoustic impedance Inverted Section

The seismic inversion generates separate P-impedance of the survey with low frequency update from well log P-impedance initial models using the model-based inversion algorithm. The low frequency impedance model is shown in Figure 2. The low-frequency impedance model has been found to have smooth changes in values along the surface and even in the vicinity of the wells, providing a more realistic geological model. It represents a low-frequency model that displays anomalies at several well locations using inverse-distance interpolation.

The inverted cross-section is presented in Figure 3 with inset gamma ray logs for wells 2, 3 and 6. The zones in red, blue and purple are in increasing order of acoustic impedances, while zones in green to yellow have low impedance values. There is a variation in acoustic impedance from 19.2 × 103 (ft/s*g/cc) to 27.1 × 103 (ft/s*g/cc). Acoustic impedance generally has high sensitivity to lithology and has the potential to fairly discriminate brine sands from hydrocarbon-charged sands. The acoustic impedance has elevated values, which ranged from 26.1 to 27.2 ×103 ft/s * g/cc with purple and blue colours corresponding to shales dominated formations. The intermediate values of acoustic impedance ranged between 22.1 and 24.1×103 ft/s * g/cc with red corresponding to shaley sands. The lowest acoustic impedance values are associated with hydrocarbon saturated sands, which have green and yellow colors in the range of 19.2 and 20.5 ×103 ft/s*g/cc. The region around Well 3 has predominately shale compared to Well 6 which is made up of hydrocarbon sands with intercalation of shale.

Training and Validation of Neural Networks

As described by Hampson *et al*. (2001), the PNN tries to find the weights that depend on the distance between the input point and each of the training points. The distance is measured in multidimensional attribute space and is scaled by smoothers (the sigma values), which are determined automatically by cross validation. Then, the weighting functions are multiplied by the known log values to determine the unknown log values. Theoretically, it can predict any log property. Practically, the software (Hampson Russel Software) can do the tasks through sequential steps.

First, the software finds the best set of attributes with the lowest prediction error using the technique of multilinear regression. For this step, the software is provided with the seismic poststack data to derive the internal attributes. Also provided are the interval velocity and post stack inversion volumes as external attributes

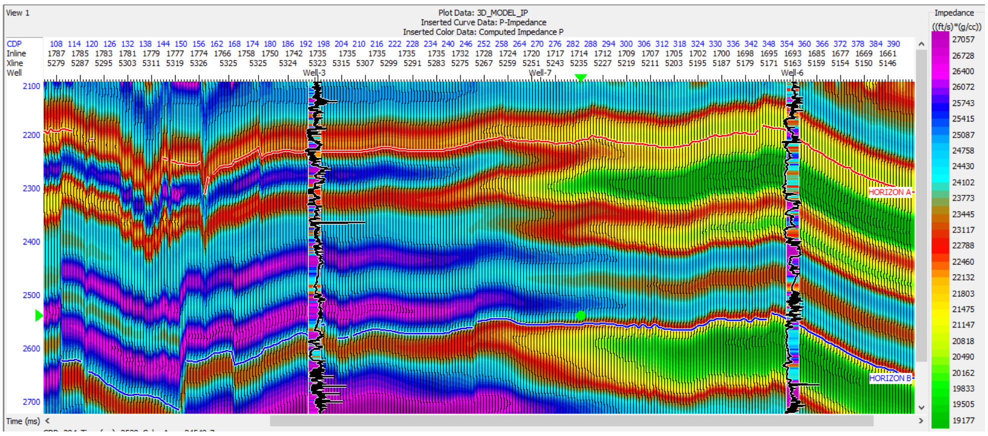

Fig. 2. Low frequency Model

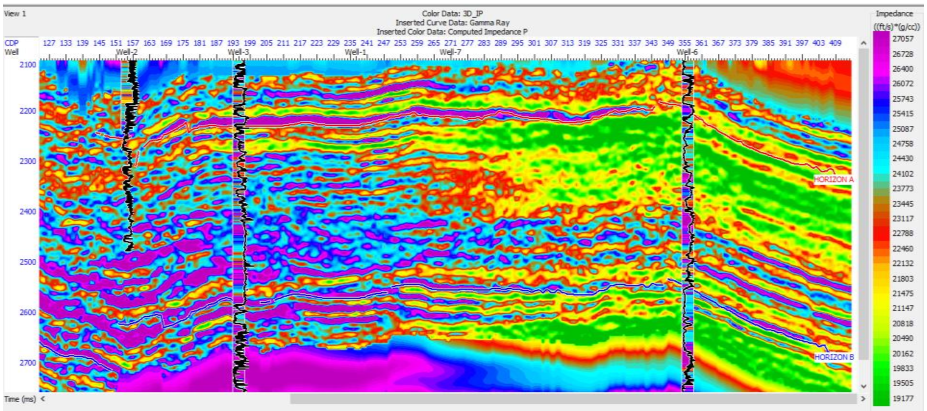

Fig. 3. Acoustic impedance cross-section results with Gamma ray logs for wells 3 and 6

The software derives internal attributes from seismic data, which can be grouped into instantaneous attributes, windowed frequency attributes, filter slices, derivative attributes, integrated attributes, and time. Those attributes are increased further by applying nonlinear transforms: natural log, exponential, square, inverse, and square root. As the frequency content of the seismic data and log data are not identical, correlating the log with the attributes on a sample-by-sample basis may not be optimal. So, we use a convolutional operator in which we relate each sample of the target log to a group of neighboring samples on the seismic attribute.

As can be seen in Figure 4 and Table 1, the minimum validation error occurs when a seven-point operator is applied with six attributes. Any other combination results in a larger validation error. These attributes are: 1/inverted P-impedance, amplitude frequency, Derivative instantaneous amplitude, dominant frequency (inverted P-impedance), filter 55/60 to 65/70, filter 55/60 to 65/70 (inverted P-impedance), derivative (inverted P-impedance), cosine instantaneous phase, integrated absolute amplitude (inverted P-impedance), filter 45/50 to 55/60 (inverted P-impedance) respectively. Using these attributes, the network was trained and validated. The PNN shows outstanding results in the prediction of porosity logs. Original porosity logs are shown in Fig. 4 together with predicted porosity values for each well, with an average correlation coefficient of 0.69. In the last step, we apply the weights from the trained neural network to the 3D seismic data volume to generate a porosity volume.

Probabilistic Neural Network (PNN) Prediction
In this study, porosity volume was estimated away from the wellbore using probabilistic neural network estimation, which can resolve non-linear interactions. Figure 6 depicts PNN Porosity Predictions in Cross-section. Figure 7 depicts Porosity predictions in map view for Horizon A using PNN. Figure 8 depicts a Porosity map for Horizon B created with PNN. Horizon A generally exhibits higher porosity values, ranging between 20 and 30%, while Horizon B has lower porosity values ranging between 16 and 26%. This implies that horizon A is generally more porous than horizon B. Higher porosity typically indicates better reservoir quality,

as it means there are more void spaces available to store hydrocarbons. Therefore, Horizon A represents a more favorable target for further exploration or development activities. This interpretation is valuable for understanding the reservoir characteristics and can have implications for petroleum exploration and production strategies.

Table 1: List of order and number of attributes that are used to train and validate the Network

Multi-Attribute List: Multi Attribute List 1

	Final Attribute	Training Error	Validation Error
1	1 / (inverted_Zp)	4.248266	4.615731
2	Average Frequency	4.087040	4.228714
3	Derivative Instantaneous Amplitude	4.031773	4.172396
4	Dominant Frequency(inverted_Zp)	4.031502	4.176122
5	Filter 55/60-65/70	4.030795	4.183821
6	Filter 55/60-65/70(inverted_Zp)	4.027154	4.206730
7	Derivative(inverted_Zp)	4.002705	4.223366
8	Cosine Instantaneous Phase	3.907874	4.222641
9	Integrated Absolute Amplitude(inverted_Zp)	3.904629	4.217271
10	Filter 45/50-55/60(inverted_Zp)	3.897549	4.236475

There are 10 attribute(s).
--- Validation criterion was used in step-wise regression.

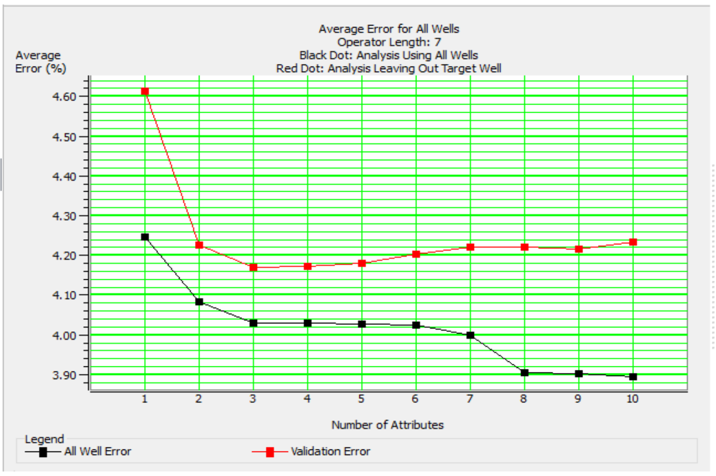

Fig. 4. Validation error plot for different operator lengths for Porosity

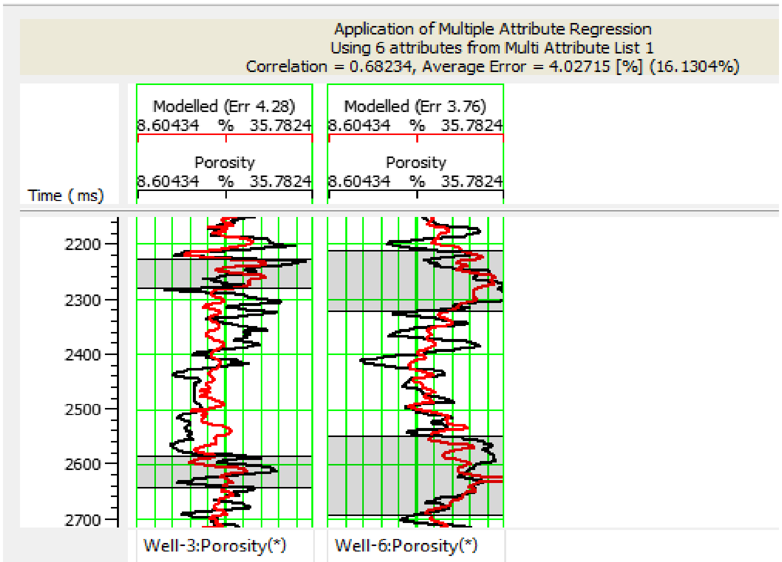

Fig. 5: Porosity (black curve) and predicted Porosity (red curve) from PNN

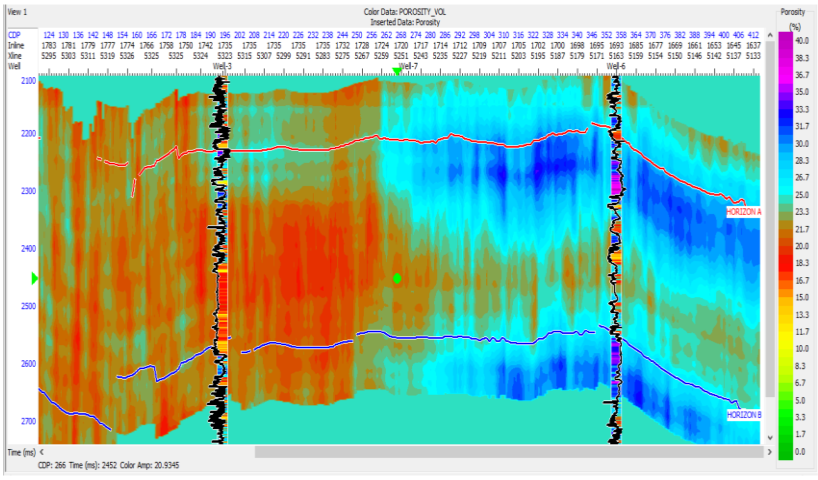

Fig. 6: Porosity Predictions in cross-section view using PNN

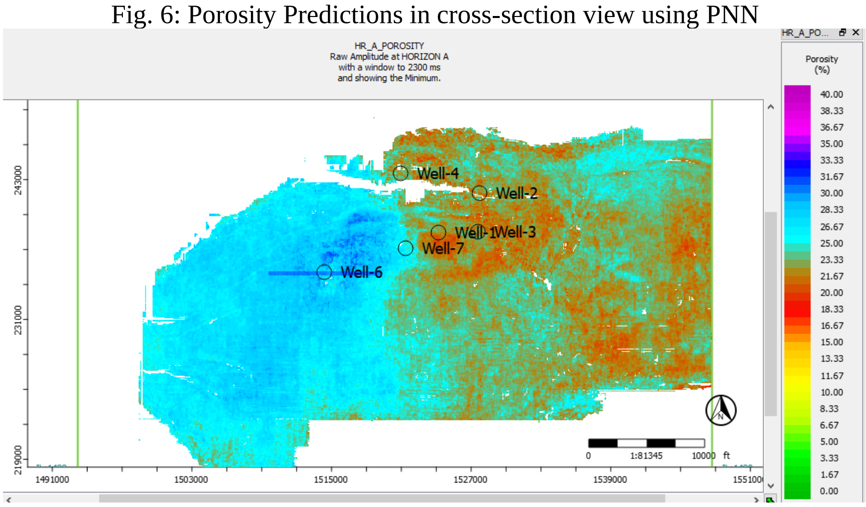

Fig. 7. Porosity predictions in map view using PNN for Horizon A

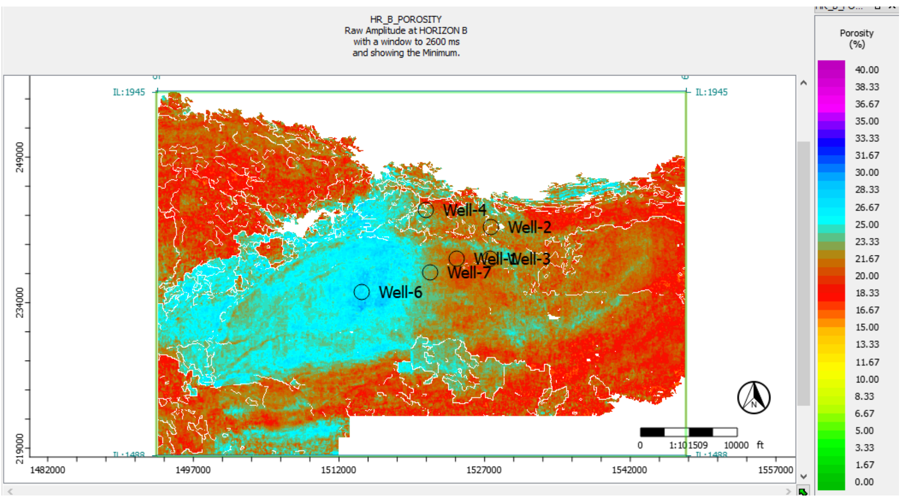

Fig. 8. Porosity map for Horizon B using PNN

CONCLUSION

The study outlines a robust strategy for improving reservoir characterisation in a Niger Delta field utilizing deep learning-assisted model-based inversion approaches. By utilizing model-based inversion, it was possible to identify important petrophysical characteristics from seismic data, which made it possible to draw boundaries around reservoirs and make geological interpretations more relevant.

Parameters like acoustic impedance were obtained by seismic inversion, which gave important information on lithology and hydrocarbon saturation. Additionally, the research shows that Probabilistic Neural Networks (PNN) are effective in forecasting petrophysical characteristics away from well sites, namely porosity and water saturation. The PNN analysis demonstrated its ability to resolve non-linear interactions and properly forecast reservoir features by utilizing seismic attributes and well-log data. The results highlight the potential of deep learning aided model-based inversion and PNN techniques in improving reservoir characterization accuracy, particularly in complex geological settings like the Niger Delta. These advancements offer valuable insights for the oil and gas industry, aiding in better reservoir management decisions and optimizing hydrocarbon recovery strategies. Overall, this study contributes to the ongoing efforts in advancing reservoir characterization methodologies, emphasizing the importance of integrating innovative techniques such as deep learning and neural networks into traditional geophysical workflows for enhanced subsurface understanding and exploration success.

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