Reservoir Permeability Prediction Using Artificial Neural Network; A Case Study of "XZ" Field, Offshore Niger Delta

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ABSTRACT

Reservoir Permeability is one of the most important characteristics of hydrocarbon bearing formations. A good knowledge of a formation's permeability helps geophysicist to efficiently manage the production process. Formation permeability is often measured in the laboratory from cores or evaluated from well test data. Core analysis and well test data, however, can only be gotten from a few wells in a field due to economic factors, while majority of wells are logged.

In this study, an artificial neural network has been designed with PETRELTM, which is able to predict permeability of a formation using the data gotten from geophysical well logs with good accuracy. A case study from XZ field offshore Niger Delta is presented. Five well log responses (Gamma Ray Log (GR), Deep Resistivity (RD), Formation Density (DEN), Neutron Porosity (PHIN) and Density Porosity (PHID)) were initially used as inputs in the ANN to predict permeability.

Core permeability from one of the wells (OS1) was used as target data in the ANN to test the prediction. The accuracy of the ANN approach is tested by regression plots of predicted values of permeability with core-permeability which is the standard. Excellent matching of core data and predicted values reflects the accuracy of the technique. Permeability estimations/predictions presented in this paper have a correlation coefficient of 0.8 where 1.0 is a perfect match. This work showed that prediction result is improved by adding core porosity in the training, carefully selecting input data and increasing the number of iterations reasonably.

(Keywords: artificial neural networks, reservoir permeability, petrel, Niger delta)

INTRODUCTION

A reservoir is a subsurface rock that has effective porosity and permeability which usually contains some quantity of exploitable hydrocarbon. Reservoir characterization involves the determination of reservoir properties/parameters such as porosity (Φ), permeability (K), fluid saturation etc. in other to determine its capability to store and transmit fluid.

Porosity is a measure of how much of a rock is open space. This space can be between grains or within cracks or cavities of the rock. Permeability is the capacity of a reservoir rock to permit fluid flow. It is a function of interconnectivity of the pore volume; therefore, a rock is permeable if it has an effective porosity. The fluid saturation is the proportion of the pore space that is occupied by the particular fluid. Rock permeability or interconnectivity of a rock pore spaces is an important parameter that determines flow ability or recovery of hydrocarbon in a sandstone reservoir. Permeability and other reservoir properties are difficult to determine because they are naturally characterized by heterogeneity, uncertainty and nonlinearity. (Bhatt and Helle, 2002)

Permeability is usually gotten by taking a core sample and measuring directly or by applying empirical models/formulas that relate permeability to parameters calculated from well logs like porosity and water saturation. The cost of undertaking the first method is very high, while in the second method, coefficients of the equations obtained for one formation does not perform well in the other fields (Mohaghegh et al., 1994).

As a result of these, it is extremely difficult to explicitly quantify spatial relationships of variable reservoir properties. However, Computer-based Intelligence methods (e.g., Neural Network, Fuzzy Logic, etc.) can correctly solve this type of complicated problem. (Ouenes, 2000; Nikravesh and Aminzadeh, 2001; Nikravesh et al., 2003).

Artificial Neural Networks

A neural network is an algorithm that takes multiple inputs and returns one or several outputs. These inputs may be coincident log values, coincident seismic attributes, coincident surface values or properties from the same cell. Each input is multiplied by a weight and is summed, and the result passed through a nonlinear function to produce the output.

Artificial Neural Networks (ANN) are comparable to biological nervous systems and consist of input layer, hidden layers and output layer (Fausett, 1994; Haykin, 1999). The architecture of an ANN includes a large number of neurons organized in different layers, with the neurons of one layer connected to neurons of another layer by means of adjusting weights.

As in biological systems, the network function is determined to a great extent by the connections between elements. A neural network is trained to perform a particular function by adjusting the values of the connections (weights) between elements. Usually, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. This process is called a learning algorithm, where the network is adjusted, based on a comparison of the output and the target, until the network output closely matches the target.

Mathematically,

$$O = F(\sum i_n W_n) \quad \textbf{(1)}$$

Where,

O = output

F ( ) = a nonlinear function

i_n= the nth piece of input data

W_n= = the assigned weight for the nth piece of input data

Comparison between Artificial Neural Network and Conventional Computer Algorithms

Unlike conventional computer algorithms which follow a set of instructions in order to solve a problem, Artificial Neural Networks learn by example and they cannot be programmed to perform specific tasks, and their operations can be unpredictable since the network finds out how to solve the problem itself; therefore the examples must be selected carefully to avoid wasting time and the network not functioning properly.

Also, since the specific steps that the computer needs to follow must be known before the computer can solve the problem, it follows that the problem-solving capability of conventional algorithms is restricted to problems that we already understood and know how to solve.

Geology of Study Area

The Niger-Delta forms one of the world's major hydrocarbon provinces, and it is situated on the Gulf of Guinea on the west coast of central Africa (Southern part of Nigeria). It covers an area between latitude 30N and 60N and Longitude 5ºE and 80E.

It is composed of an overall regressive sequence, which reaches a maximum thickness of about 12km.It ranks among world's most prolific petroleum producing Tertiary deltas that together accounts for about 2.5% of the present-day basin areas of the earth. The Niger Delta is among the world largest regressive sequence with a thickness of over 12000m and occupies an area of 7500km^2 (Whiteman, 1982).

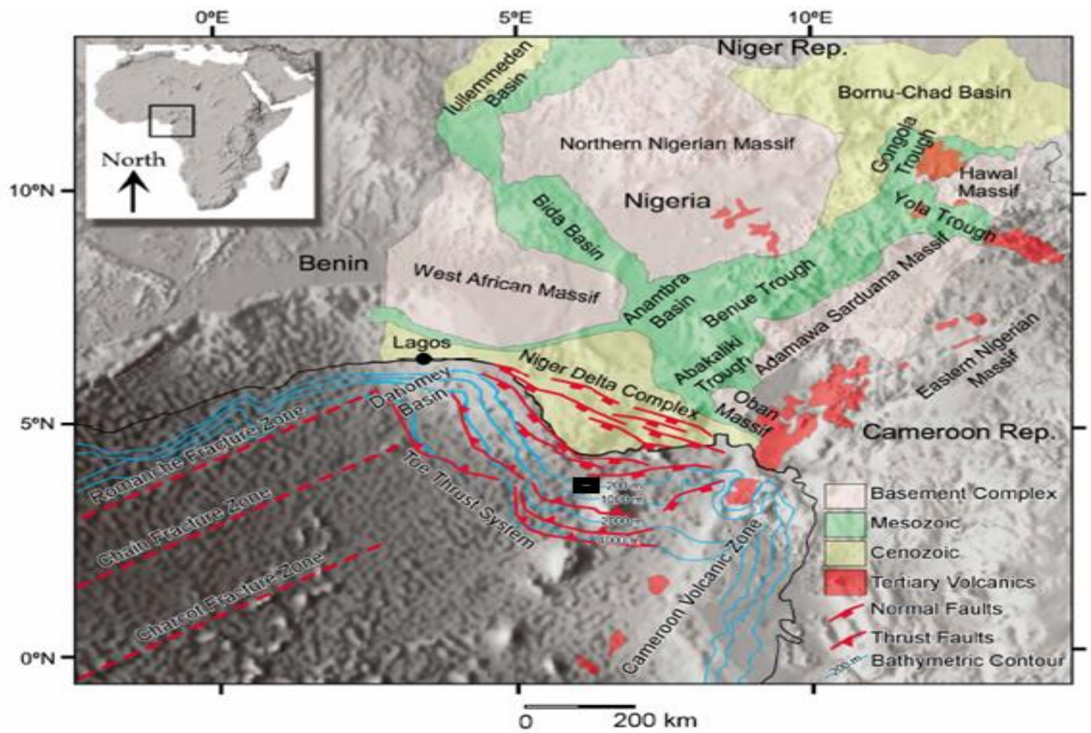

Figure 1: Map of Niger Delta Showing the Study Location.
■ Study location

MATERIALS AND METHODS

The dataset used for this study was acquired from Addax Petroleum Development Company. It includes 3D seismic reflection data, suites of composite logs from three wells and check-shot data. All the data files are in standard digital format which include:

i. Base map
ii. Well header (ASCII)
iii. Deviation data (ASCII)
iv. Composite well logs (ASCII): These logs include Gamma ray (GR), Resistivity (RES and LLD), Neutron (NPHI), and Density (RHOB).
v. Microsoft office tools (Excel, Paint and Note pad)

The Neural Network toolbox available on PETREL™ version 2014, a Schlumberger product for reservoir characterization and visualization of seismic models was used. Permeability Prediction was carried out on a work station using the Neural Network Toolbox.

PETREL™ Neural Network is a Windows based user-friendly software. The following processes were carried out:

(i) Well log Data import
(ii) Artificial Neural Network Training, Testing and Validation
(iii) Permeability prediction and Cross Plot Validation

Permeability Prediction

First step is the preparation of well logs data and applying ANN on the data. The data sets used in this part of the study were derived from some wells of the studied field in which one of the wells (OS1) has core permeability data which was utilized for constructing the ANN model. The model was then used to predict permeability logs in uncored intervals in well OS1, and two other wells (OS3, and OS5).

The given data was properly studied and then stored into a compatible standard format. Various folders were created e.g. the well top, well header and time depth conversion files. All the data files are stored in a location on the PC, from where it was accessed. Before the interpretation process, PETREL™ workflow must define folders, this is symbolic. Some of the data were imported into this or into user- defined ones. The algorithm was set so as to obtain the required output.

Well Log Data Import

The sequence of data import begins with the well heads, deviation and logs. The well heads file contains the well name, surface location of the wells (2D-XY coordinate system), Kelly bushing (KB), the top depth, bottom depth and the measured depth (MD). This will allow the display of well position on the base map. To the well head, the deviation data is attached, which defines the path of the deviated wells according to their measured depth respectively. The logs are then imported; attached to the well head and deviation data.

Artificial Neural Network Model Training, Testing, and Validation

Training Estimation Model: Neural network method in petrel was accessed through The Train Estimation Model sub-menu of the Utility menu. Well log OS 1 was the input data provided for training. The process computed an estimation model that responded in a similar way when presented with similar input data. The estimation model in turn was used in the modeling process.

Training Supervised Neural Networks: The training data was provided as input-output pairs. In the train estimation model process, the data pairs were used to make a model (function) that estimated the correct output data when presented with the given input data. The idea was that the same model (function) can then be applied to similar input data to compute reasonable output.

The error in the network was assessed by passing the training data's input through the neural network and comparing it to the original data. The error was reduced through a process called back-propagation (Rumelhart and McClelland 1986). In this work, supervised training was used in combination with Estimation which involved computing missing log data in a well based on known values in some parts of the well.

A simplified workflow of the algorithm is summarized below:

1. Initialize the network weights to small random values
2. From the set of training input/output pairs calculate the network output
3. Make a Comparison between the computed output and the target output (i.e., core permeability from OS1). The difference at each iteration is flagged as error
4. Update the weights of the network
5. Repeat step 2 to 4 until a minimum overall error is obtained (training)

The following were noted in the algorithm during training:

(i) Max Number of Iterations – The program iteration was started at 2000 then gradually increased until a reasonable correlation was gotten at 5000. The algorithm stopped at this number even when an adequate result has not been reached.

(ii) Error Limit (%) – 20% was stated. When the number of points classified incorrectly was below this limit, model was assumed to be trained and will stop.

(iii) Cross Validation (%) - 50%. This is the percentage of the input data which is used to test the result and give the error. The remaining part is used to train the model.

Cross Validation

OS1 well log, the data used for supervised learning was split in two parts, 50% for training and cross validation respectively. Therefore, 50% of the core permeability was used together with all the input logs to establish an estimation model that computed a permeability log which was present in all points (the training points and for the cross-validation points). This allowed for comparing the model with both point sets, hence, ensuring quality of the estimation model. This is also to ensure that a general relationship was being established and not just a perfect match with the available core permeability we already have.

This model was then used for predictions in wells OS-3 and OS-5. The generated predicted permeability from the set of input data was compared with core permeability to determine correlation and their similarity. This was done by fitting a linear regression line using least square approximation method. A good correlation coefficient between both logs would indicate that the predicted log has an improved accuracy and hence most likely gives spatial realistic geologic information where there is no core data.

RESULTS AND DISCUSSION

Log responses used in this study stems from the fact that they were available for wells OS 1, OS 3 and OS 5 which was used for the training and predictions. In order to see accurate and repeatable results in the design and development of neural network for permeability prediction, it is important to have enough training data.

After plotting core measurements against network model predictions, a slight divergence is seen from a perfect match, which is the unit slope line. This shows the network was able to follow the trend even though permeability values cover a wide range. Permeability estimations and predictions presented in this paper have a correlation coefficient of 0.8, where 1.0 is a perfect match (Figure 5).

Comparison of the results presented in Figures 2–5 reveals the power of artificial neural networks in pattern recognition. Carefully selecting input data improved the results shown is Figure 2 – Figure 5.
Also adding core porosity to the training data set gave excellent results (Figure 5).

Figure 6 shows generated lithofacies log estimated from the GR log and the vertical variation of lithologies within the formation. It also shows the permeability responses at areas where core data was absent indicating that some hydrocarbon bearing sandstone units penetrated by the well have good permeability values hence increased flow-ability and hydrocarbon recoverability.

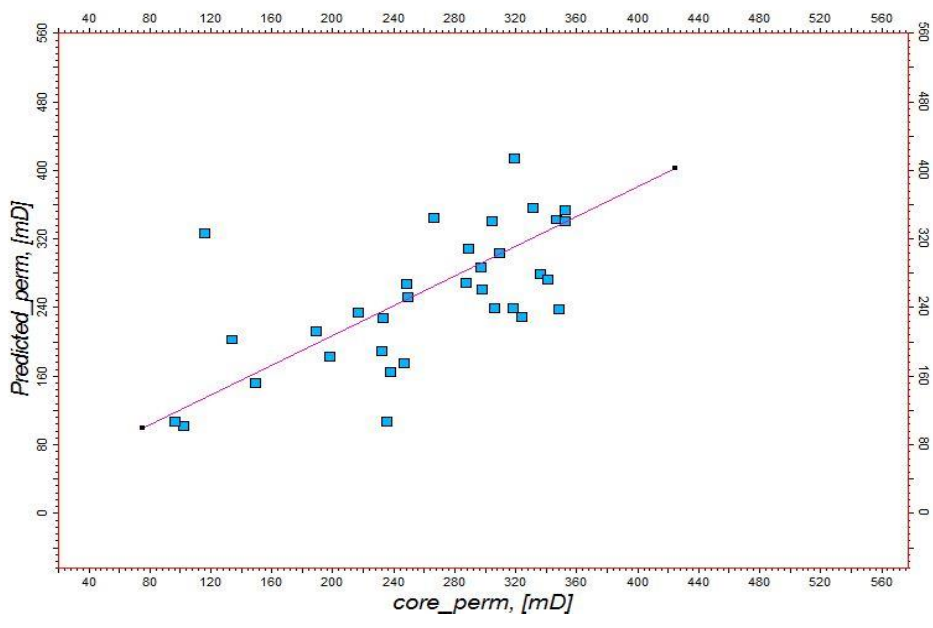

Figure 2: Cross-Plot of Permeability ANN versus Core Permeability using ANN in Training Set 1 (Correlation Coefficient 0.72).

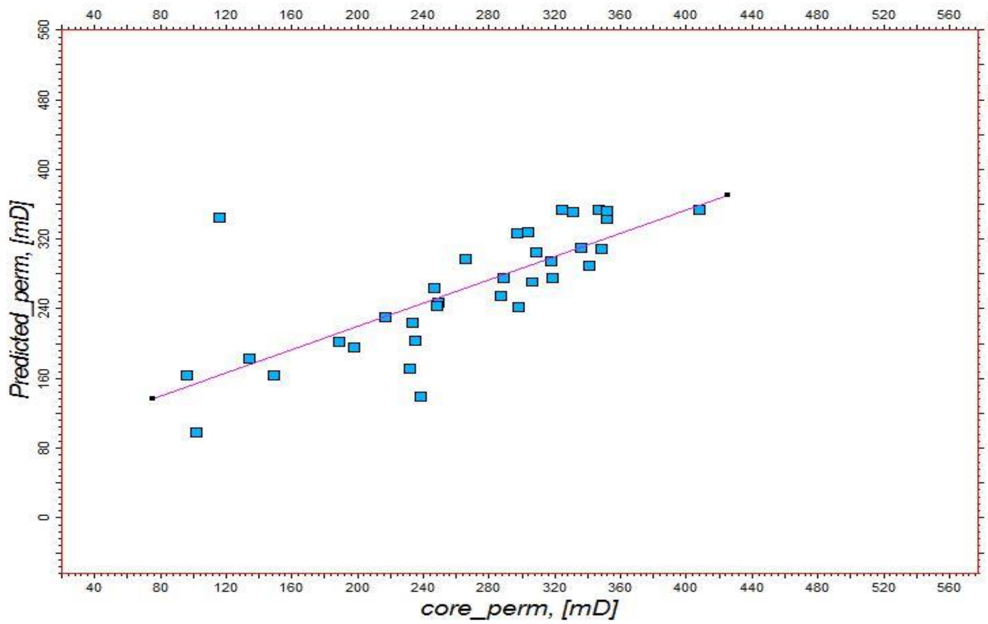

Figure 3: Cross-Plot of Permeability ANN versus Core Permeability using ANN in Training Set 2 (Correlation Coefficient = 0.75)

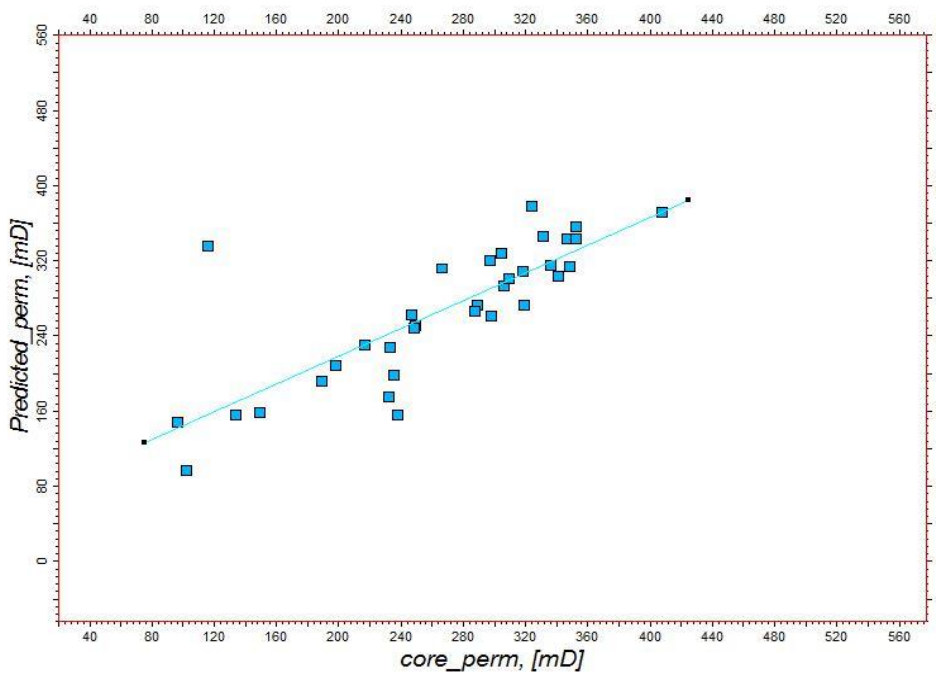

Figure 4: Cross-Plot of Permeability ANN versus Core Permeability using ANN in Training Set 3 (Correlation Coefficient = 0.79)

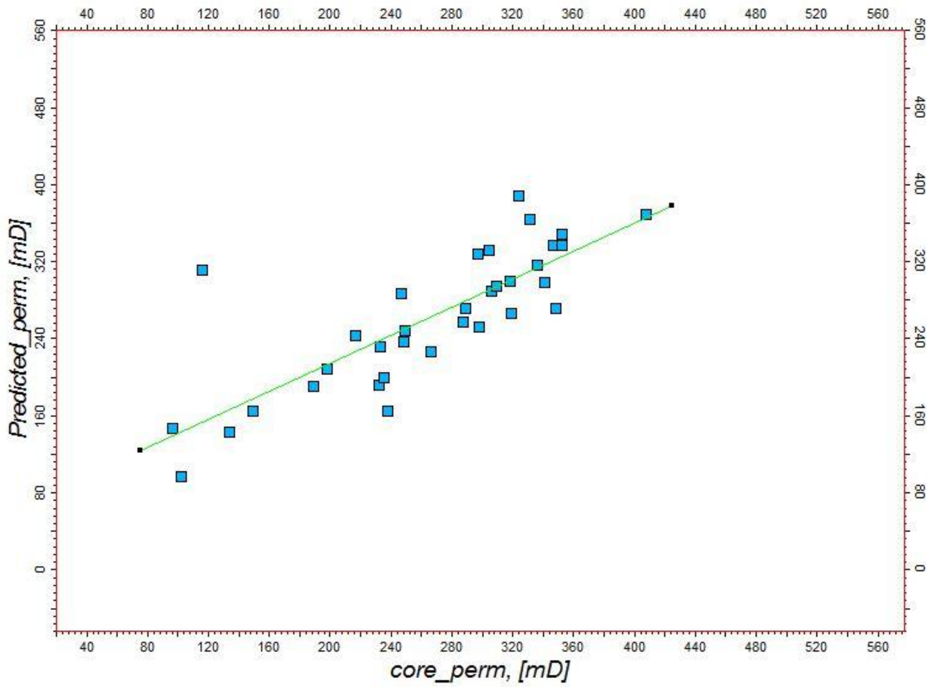

Figure 5: Cross-Plot of Permeability ANN versus Core Permeability using ANN in Training Set 4 (Correlation Coefficient = 0.80)

Estimated Permeability of Study Well

Figures 7 – 8 show predicted permeability logs for wells OS-3 and OS-5 using sets of inputs logs trained and calibrated by core permeability in well OS-1.

There are now permeability values for sandstone facies which had no core data originally. Therefore, an overall evaluation of the sandstones can now be made in the future and those that have high permeability noted.

Since high permeability indicates high flow-ability and rate of fluid transfer, the ease of hydrocarbon recoverability will be high if present.

CONCLUSIONS

An artificial neural network that is capable of predicting/estimating formation permeability, using geophysical well log data was presented. It was shown that the trained network is able to predict/estimate Permeability comparable to that of actual core measurements.

The permeability predictions improved significantly when a core data (core porosity) was among the input data. Availability of reliable core data for training process was proven to be essential. Also the presence of same log data in both the training well and wells whose prediction is to be carried out was essential for accuracy and reliability.

Adequate knowledge of fundamental theories and practices of artificial neural networks are required to achieve acceptable and repeatable results.

It is recommended that a 3D seismic post-stacked data be integrated with this result in the sand facies so that sandstone hydrocarbon bearing facies can be accurately evaluated and the lateral extent determined with estimation of the volume of hydrocarbon present.

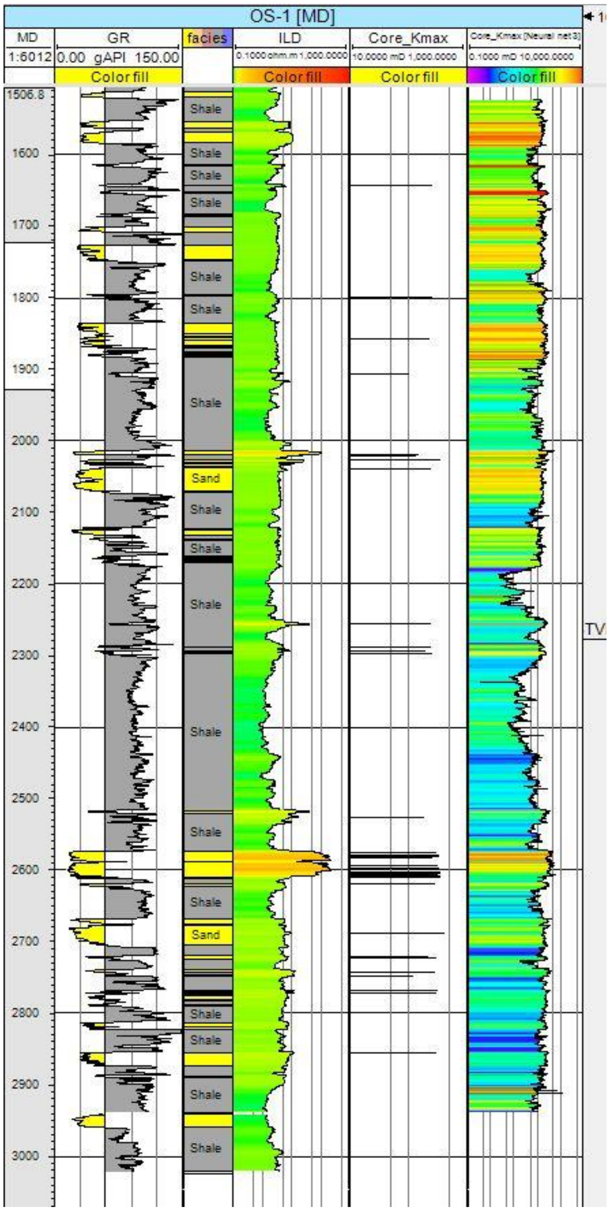

Figure 6: The Different Facies Penetrated by Well OS-1 within the Field.

(Predicted permeability logs for un-cored intervals are shown on the last track)

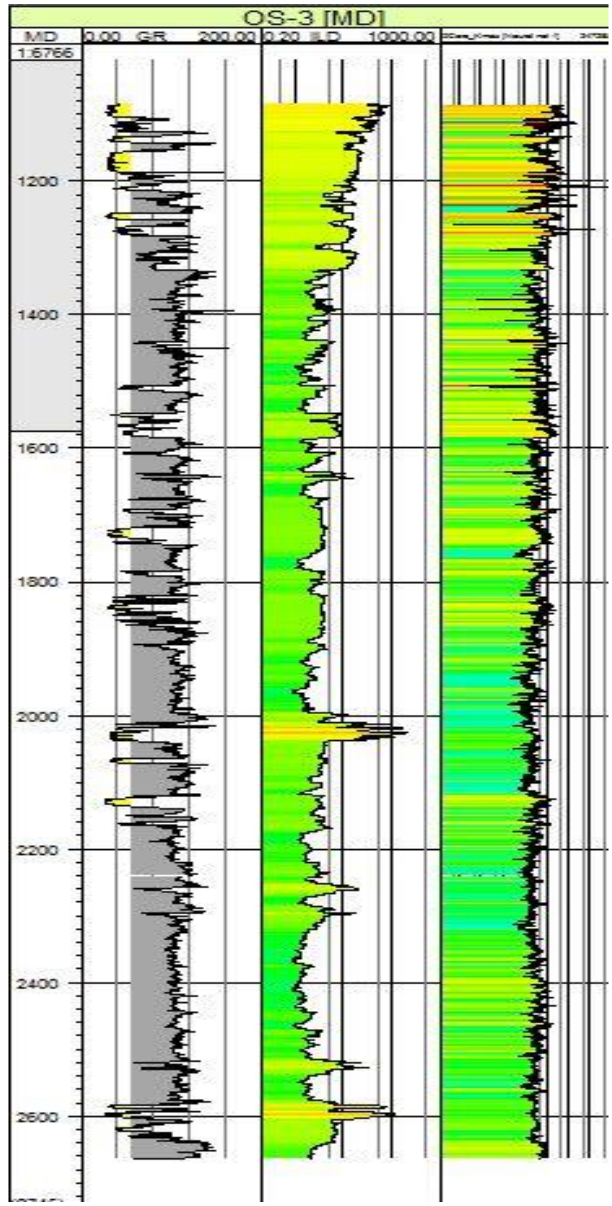

Figure 7: Permeability Logs Predicted at Well OS-3 at Various Depths.

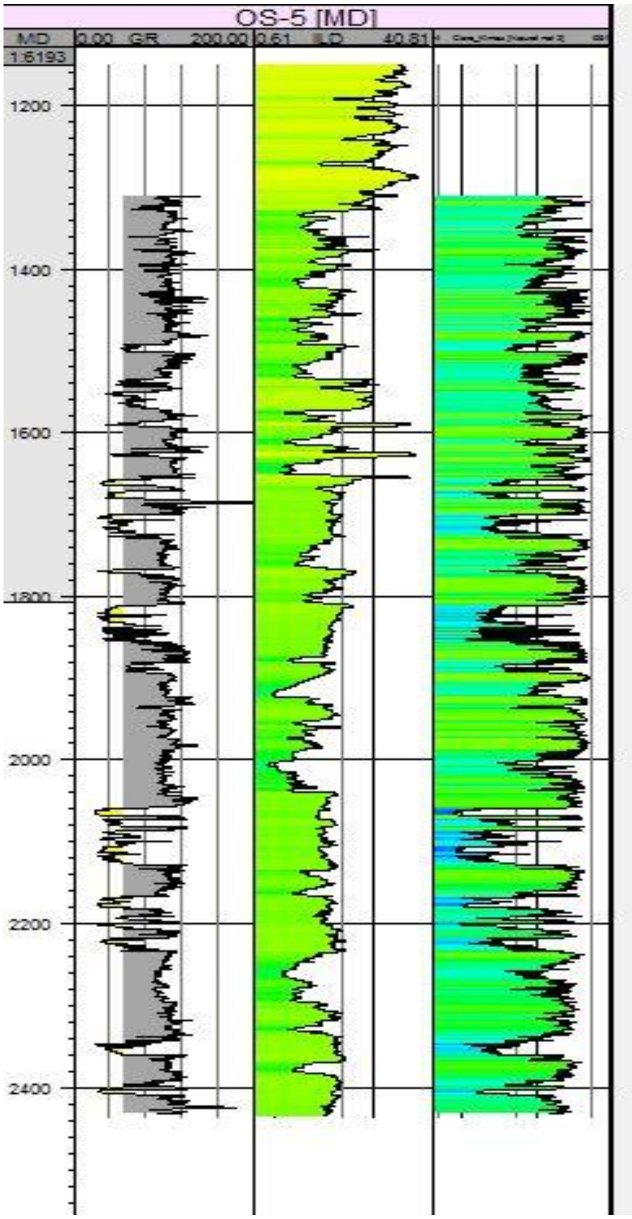

Figure 8: Permeability Logs Predicted at Well OS-5 at Various Depths.

At present, the results presented here are applicable to the study field only. However future work needs to be carried out on prediction of rock properties without the availability of core data. This would be an interesting area of research with the potential of further reducing the cost of oil exploitation and exploration, thereby helping companies save capital for other areas of production.

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