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Research Article

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The Use of Train Estimation Tool in the Reconstruction of Missing Log Intervals for Developing Stratigraphic Models: A Case Study of Anambra Basin

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Abstract Prospecting for hydrocarbon has become difficult and expensive in recent times, as such the need to ensure accurate lithological description and reservoir characterization. Train estimation model enables the use of neural networks in estimating properties and probabilities. Lithology can be isolated and classified along the wellbore, based on acquired and interpreted logs, and missing logs can be estimated based on other wells present in the project. Combining and integrating different data objects or attributes with geological concepts and analogs, increases the level of interpretation confidence and accuracy during reservoir modeling, thereby enabling realistic reservoir characterization. The understanding of stratigraphic architecture, the complexity of both reservoir rock and fluid properties is essential and controls the initial quantities, distribution of hydrocarbons and the rate of flow of these fluids within the reservoir, as well as the recoverable volume of hydrocarbons. This paper demonstrates the use of ditch cuttings along with log curves in the lithologic classification and the estimation of missing log intervals using neural network in Train Estimation Model (TEM) for the purpose of building stratigraphic models that will enable more accurate prospect identification.

Keywords Reservoir, Well log, Train estimation model, Artificial neural network

Introduction

Reliable prediction of reservoir permeability is an important of reservoir performance assessment and management. Although many algorithms have been derived regarding permeability and porosity in sandstone reservoirs, correlations are most accurately depicted for the wells that are cored and with well test data. Well logging is considered as an integral part of formation evaluation that can provide great amount of data, which can be the best candidate to help in stages in developing reservoir static and dynamic models for efficient production and economic recovery [1]. But, it is quite common for the log records to be missing due to many reasons such as broken instruments, borehole conditions, instrument failure, or loss of data due to inappropriate storage and incomplete logging [2-3]. This can result in the absence of some logging intervals or even an entire log type. Therefore, it is appeared that finding a new method for estimation of these parameters is necessary. For this purpose, many studies have been focused on prediction of the wire-line logs. Most of these studies have been tried to propose an intelligent model using artificial intelligence (AI) techniques. The artificial intelligence techniques have the remarkable ability to establish a complicated mapping between non-linearly linked input and output data.

Therefore, having a framework for estimation of these parameters in reservoirs with neither coring samples nor well test data is crucial. These properties are characterized by using different well logs. However, there is no specific petrophysical log for estimating rock permeability; thus, new methods need to be developed to predict permeability from well logs. One of the most powerful tools that were applied by the authors is artificial neural network, whose advantages and disadvantages have been discussed by several authors [4-7]. Multilayer neural network was applied to develop an intelligent predictive model for prediction of the logs. This forms the framework or principle of Train Estimation Model (TEM) deployed for lithofacies classification and reservoir properties estimation.

Lithofacies classification based on experimental data is one of the important problems in geophysical well-log studies. Since permeability and fluid saturation for a given porosity varies considerably among the lithofacies at a certain depths, classification of lithofacies and their adequate representation in a 3-D cellular geophysical/geological model is vital for understanding the crustal inhomogeneity, the permeability, and the fluid saturation for exploration of oil and gas. The best sources of lithofacies information are core samples of reservoir rocks collected from wells. However, cores are not commonly taken due to high costs. The availability of core samples is also limited in comparison to the number of drilled wells in the geological/geophysical field. Hence, in a situation where core information is not available, the down-hole geophysical logs can be used as an alternative to infer the nature of surrounding rocks/lithology.

The use of Train Estimation tool is good for automatically finding relationships between multiple known parameters and a single potentially unknown parameter [8-9]. This tool can be used to identify the relationship between facies and other measured logs. The established relationship can then be used in any well to estimate the unknown parameter where the input logs are present.

In this study, Train Estimation tool was applied on eight (8) wells in the study area, with some of the wells sections and/or intervals having poor or non- available log data. The available logs were trained to generate synthetic log curves in areas with poor or missing wire line logs based on the results from Principal Component Analysis (PCA) and Correlation Analyses (CA) and supervised by the particular log type to be trained. Lithologies were isolated and classified to generate lithofacies logs from the estimated or trained logs along the wellbore and were calibrated with interpreted lithologies from ditch cuttings for the studied wells. These synthetic log curves provided enhanced geologic information and therefore enabled the construction of reliable stratigraphic models and will therefore enhance the development of new hydrocarbon plays within the Anambra Basin.

Study Area

Anambra Basin is one of the Cretaceous sedimentary basins of Nigeria, bounded on the southwestern flank by the Niger Delta hinge line, northwest by the Benue flank and southeast by the Abakaliki fold belt. The basin lies between latitudes 00005.0N and 8.0N and longitudes 6.3E and 8.0E. The basin is one of the intra-cratonic basins in Nigeria considered by some authors as the Lower Benue Trough, a NE-SW trending, folded, aborted rift basin that runs obliquely across Nigeria (Figure 1). Its origin was linked to tectonic processes that accompanied the separation of African and South American plates in the Early Cretaceous [10-11]. The basin is roughly triangular in shape and covers an area of about 40,000 square kilometers with sediment thickness increasing southwards to a maximum thickness of about 12,000m in the central part of Niger Delta (Figure 1). The dominant lithologies in the Anambra Basin comprise sandstones, shales, limestones and coal seams of Upper Cretaceous to Recent sediments and the reservoirs are vertically and laterally extensive in most parts, but not generally continuous due to some syndepositional structural complexities especially during Early to Late Maastrichtian times that may have resulted in truncations of the processes of sediments deposition.

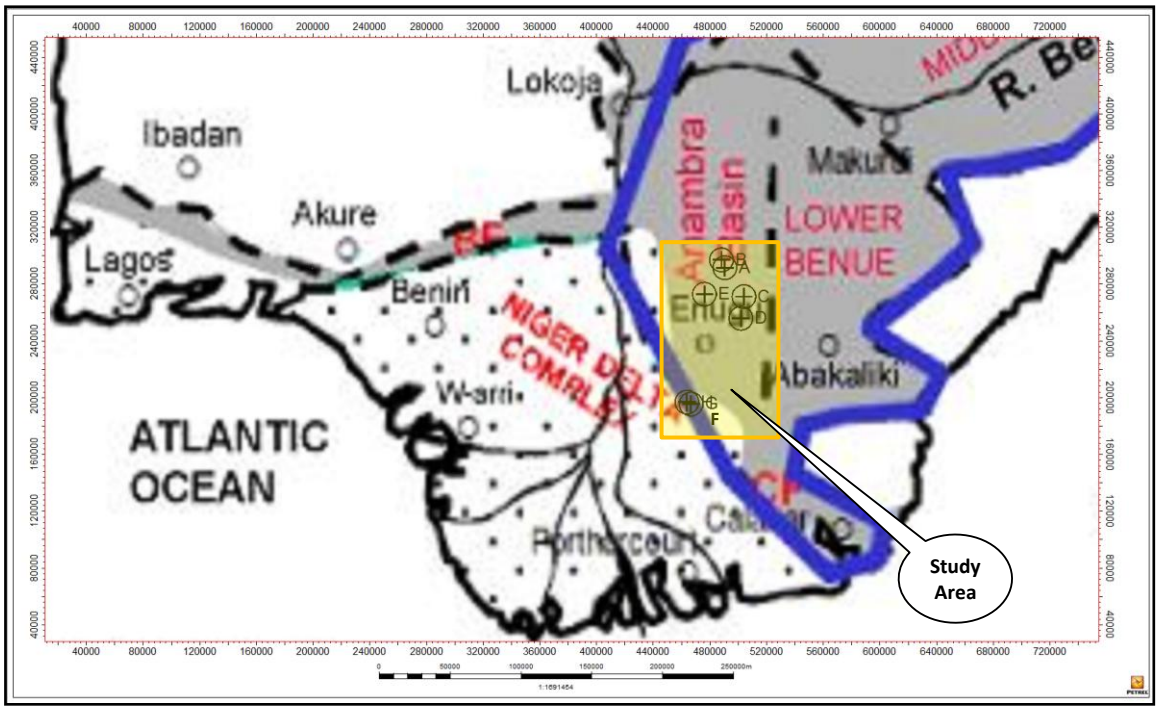


Figure 1: Location Map of the Study Area in Anambra Basin

Materials and Methodology

A total of eight wells located within the Anambra Basin were used for this study (Figure 1). Wire line logs and lithogic data of these wells were also available.

Neural nets were created in Petrel software using five input well logs (GR, NPHI, RHOB, LLD and DT) and the degree of variance between them. The structure is based on neuron which is a module of computation, takes input from available logs, performs some computation on the input and then produces output along the well interval. There are two types of training algorithms; supervised (desired output is known) and unsupervised (output comes about somehow). When neural nets are trained, they develop an estimation function learned through the experience during training. The classification ranges are predefined; 0.0 - 0.4 (Poor), 0.5 - 0.8 (Fair) and 0.8 – 1.0 (Good) [12]. They can capture subtle relationship among inputs and deal better with noisy data than other prediction methods. Therefore their use in heterogeneous reservoir is profound and valuable.

Results

The eight wells used in this study and the available wireline logs data for each of the wells are presented in the table below.

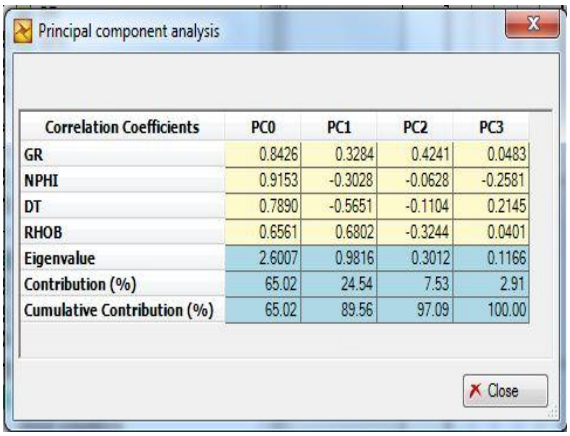
Well A has the four logs but the Neutron log data was missing within the upper section of the well (Figure 2). Well B had the four logs within the drilled interval and therefore provided a control in the log estimation for the other wells (Figure 4). Well C and D had only three logs with non availability of Bulk density logs. In addition, the porosity logs were missing within some sections of the well. Well E had no neutron log and part of the bulk density log was missing within the upper section of the well.

Table 1: Availability of the input logs data

S/N.	Well Name	Available Wireline Logs				
		Gamma Ray (GR)	Neutron Porosity (NPHI)	Bulk Density (RHOB)	Sonic (DT)	Resistivity (ILD/LLD)
1.	A	✓	NIL	✓	✓	✓
2.	B (Control)	✓	✓	✓	✓	✓
3.	C	✓	✓ *(missing intervals)*	NIL	✓	✓

4.	D	✓	✓ *(missing intervals)*	NIL	✓ *(missing intervals)*	NIL
5.	E	✓		✓ *(missing intervals)*	✓	✓
6.	F	✓	✓	✓ *(missing intervals)*	✓	✓
7.	G	✓	✓	✓	✓ *(missing intervals)*	✓
8.	H	✓	✓ *(missing intervals)*	✓ *(missing intervals)*	✓	✓ *(missing intervals)*

Principal Component Analysis (PCA) and Correlation Analysis (CA) between the input logs was carried out for all the wells, depending on which input data is available (Figures 2a, 2b & 2c), and the output is the neural net as shown in Figure 2c below. The relationships established between the input logs during the classification process are then used to estimate log facies for the missing log intervals and other wells that some of the logs were not available.



Correlation Coefficients	PC0	PC1	PC2	PC3
GR	0.8426	0.3284	0.4241	0.0483
NPHI	0.9153	-0.3028	-0.0628	-0.2581
DT	0.7890	-0.5651	-0.1104	0.2145
RHOB	0.6561	0.6802	-0.3244	0.0401
Eigenvalue	2.6007	0.9816	0.3012	0.1166
Contribution (%)	65.02	24.54	7.53	2.91
Cumulative Contribution (%)	65.02	89.56	97.09	100.00

Figure 2a: Output of Principal Component Analysis (PCA) of the logs data for one of the studied wells

	GR	NPHI	DT	RHOB
GR	1.0000	0.5012	0.3100	0.4778
NPHI	0.5012	1.0000	0.7920	0.1277
DT	0.3100	0.7920	1.0000	0.1066
RHOB	0.4778	0.1277	0.1066	1.0000
Total	0.6522	0.8403	0.8192	0.5616

Figure 2b: Output of the Correlation Analysis (CA) of the logs data for Well A

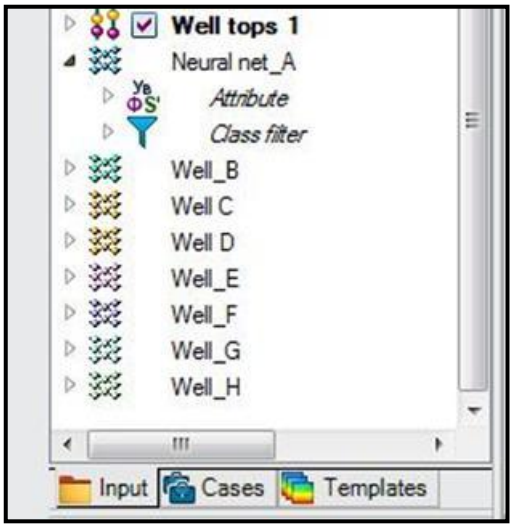
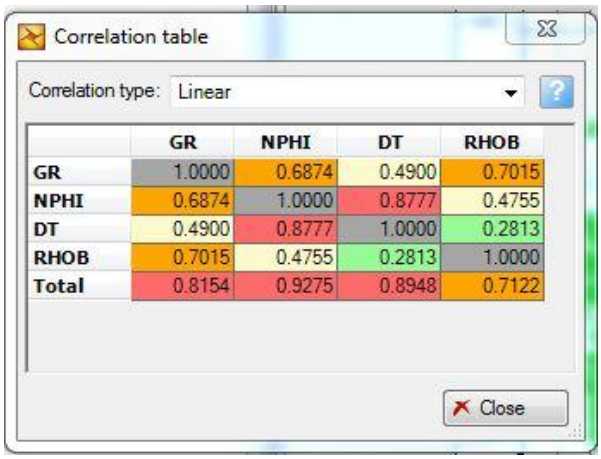


Figure 2c: Neural nets created for all studied wells from input data



	GR	NPHI	DT	RHOB
GR	1.0000	0.6874	0.4900	0.7015
NPHI	0.6874	1.0000	0.8777	0.4755
DT	0.4900	0.8777	1.0000	0.2813
RHOB	0.7015	0.4755	0.2813	1.0000
Total	0.8154	0.9275	0.8948	0.7122

Figure 2d: Output of the Correlation Analysis (CA) of the logs data for Well B

From Figures 2a & 2b above, principal component analysis and correlation analysis demonstrate that there is fair to good correlation between gamma ray (GR), neutron porosity (NPHI) and density (RHOB), where you have correlation coeficients between 0.6 – 0.9 for principal component analysis and between 0.6 – 0.87 for log

correlation analysis (Figures 2a & 2b). These means that any one or two of the three logs can be used to train any of the other missing one. Similarly, there is a good correlation between neutron porosity (NPHI), gamma ray (GR) and sonic (DT) logs (Figure 2d). Once the artificial or synthetic log model is made for lithofacies prediction using these logs correlations, we can predict lithofacies in the missing wells/sections.

Artificial neural network structure is shown in Figure 2c. The structure is based on neuron, which is a module of computation that takes input from dendrites, performs some computation on the input and then produces output along

the axon. There are two types of training algorithms supervised (desired output is known) and unsupervised (output comes about somehow). In this study, the supervised algorithm was deployed as shown in the Figure 3.

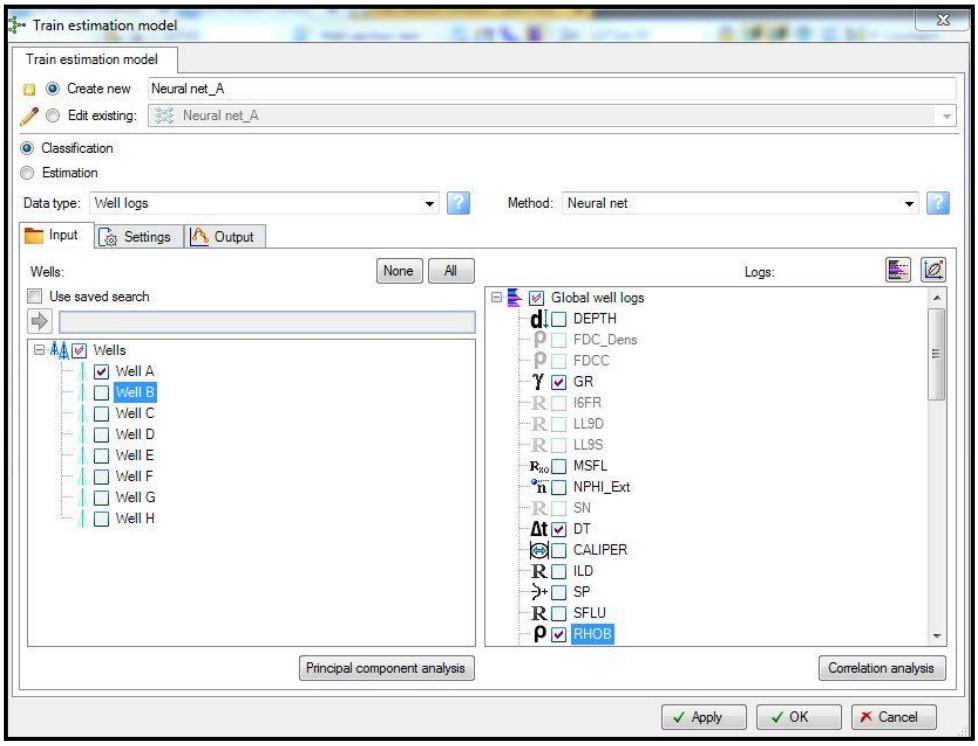


Figure 3: Train Estimation showing Principal Component Analysis (PCA) and Correlation Analysis (CA) processes

According to Hecht-Nielson [9], it is recommended to apply at least two log sets of data during the set of training estimation process.

Gamma ray (GR) and density (PHOB) logs are the most significant logs in lithofacies identification, but remedied usually by density and sonic logs, where there are overlaps [8].

Figure 4 shows the actual lithofacies log derived from lithologies described from ditch cuttings and they compared to the predicted lithofacies derived from the trained logs. The lithofacies predicted by the model are reasonably good, especially in the missing section of the well. As most oil & gas production wells have these challenges through reservoir intervals, the successful prediction of lithofacies by train estimation is of considerable value. This was calibrated with data in Well B which had all the key logs data for lithofacies interpretations (Figure 5).

Distribution and identification of lithofacies is essential as they provide qualitative information about reservoir. Every single reservoir has several lithofacies and each lithofacy has its own porosity-permeability relationship [13].

To predict the Sonic log (DT), density log (RHOB) and neutron log (NPHI) were used as input data (Figure 5). Their results indicated accuracy of the proposed method as demonstrated in Well D.

The train estimation tool was used in estimating the neutron and density logs to cover the missing intervals in Well A, C, D and E. In addition, neutron log was estimated for the entire well section of Well E (Figure 6). For

performance evaluation of the proposed model, density log was estimated using gamma ray (GR) and neutron porosity (NPHI) as input data.

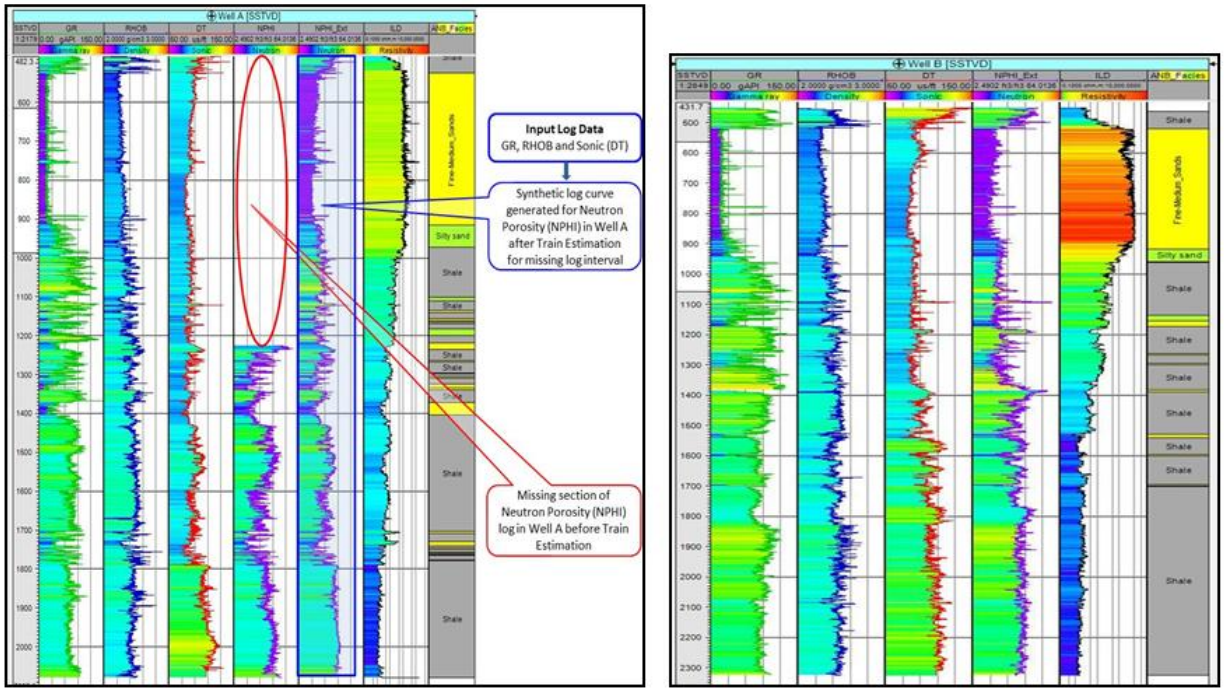


Figure 4: Well Section window showing available logs data for Well A and B displayed on Petrel platform for reference

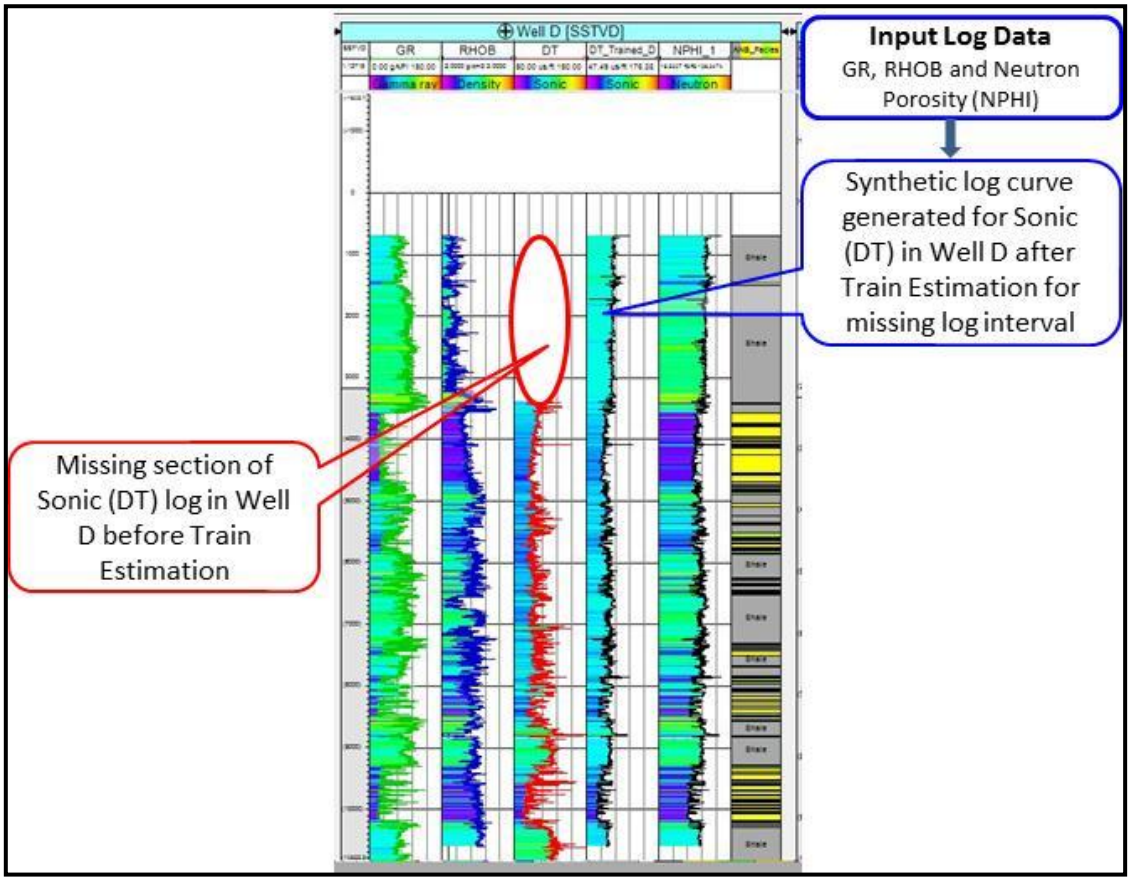


Figure 5: Well Section window showing available logs data in Well D displayed on Petrel platform

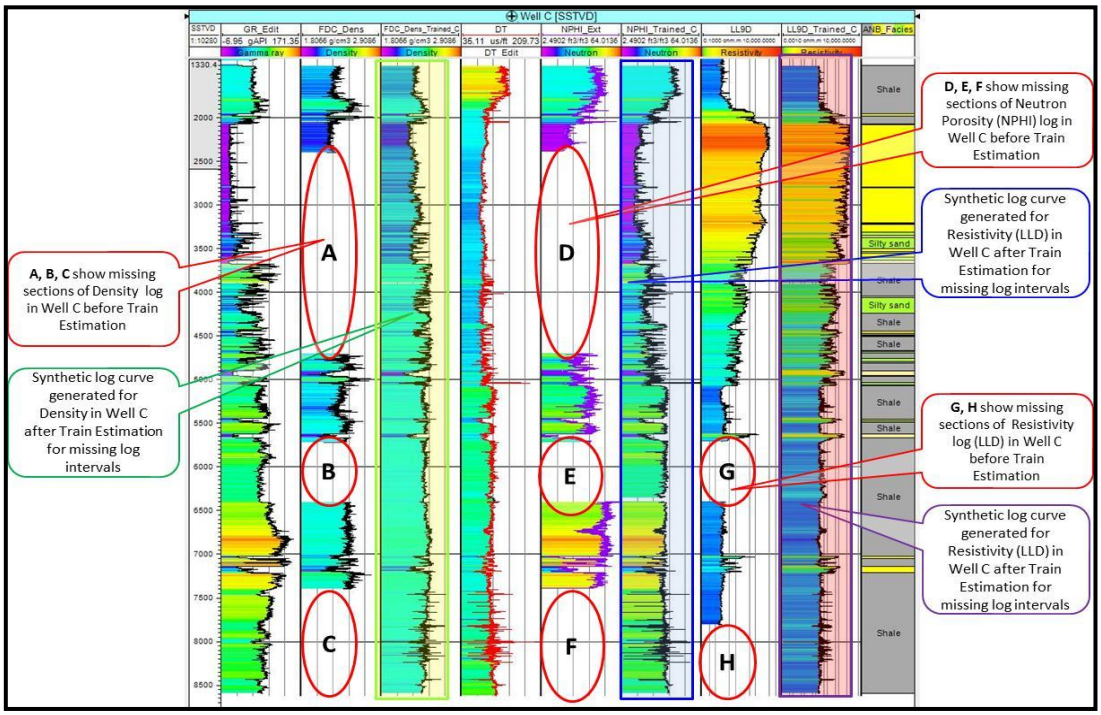


Figure 6: Well Section window showing available logs data for Well C with missing interval of the three key wireline logs and the trained logs

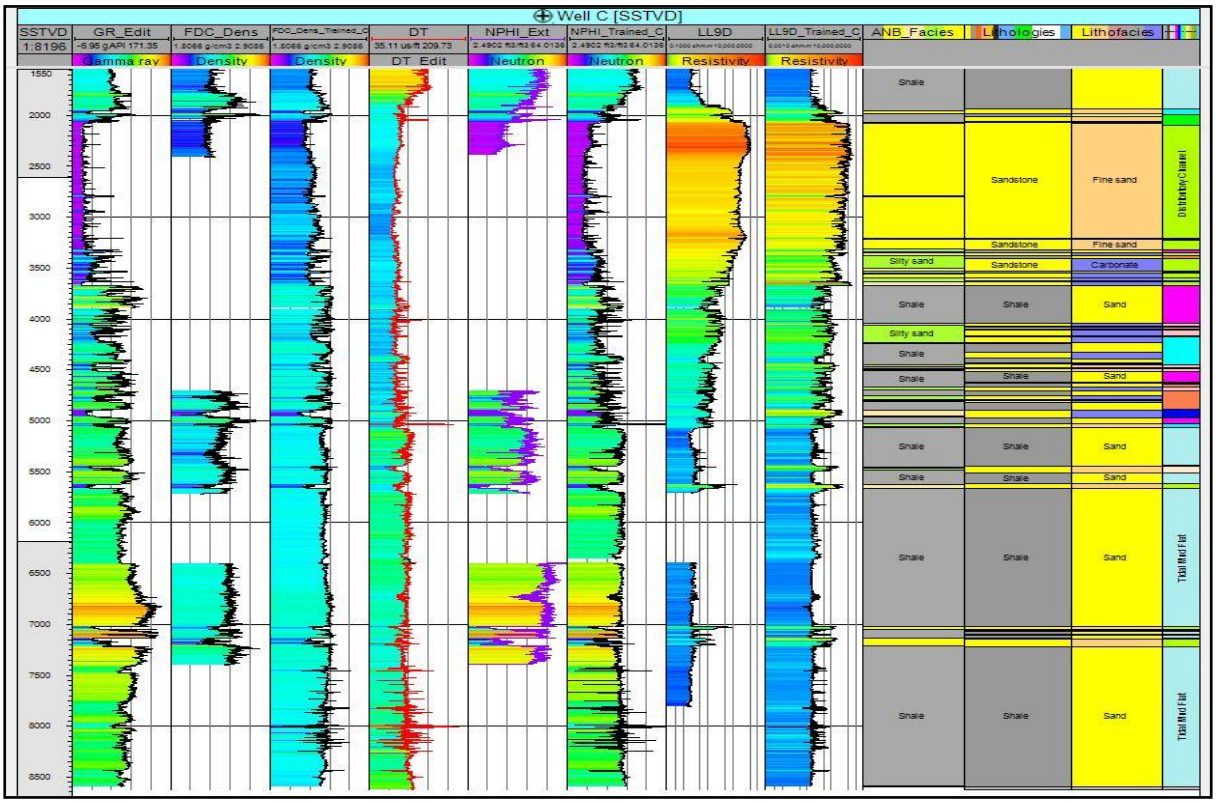


Figure 7: Well Section window of Well C, highlighting lithologies from ditch cuttings compared with lithofacies interpretations based on the GR logs and interpretation of environments of deposition based on derived or trained logs for part of the missing interval of three key wireline logs and the trained logs

Discussion/Application

In this work we have focused on presenting the development of a new classification technique which has the potential of improving facies interpretation from well logs. Since we apply the method to real data, indicating overall good performance from the trained logs, these compared well with the lithologies described from ditch cutting samples for all the eight studied wells and lithofacies interpretations from wells with complete logs data (Figure 7), as well as with those of similar studies published in the current literature.

Log sets for interpretation and characterization of lithofacies as building blocks for reservoir characterization have been optimized using synthetic logs and applied the same network architecture and techniques to facies zonation of some selected formations in the Anambra Basin. Classification from real data was more challenging since the log facies in the present study were mostly discontinuous. Application to the train estimation tool which utilizes the artificial neural network algorithms on the eight studied wells have demonstrated improved performance for lithofacies interpretations and classification (Figure 7).

The combination of the density and neutron logs provides a good source of porosity data, especially in facies of heterogenous lithology. Density log (RHOB), could differentiate if the matrix of the facies is tight or not, and could be used to differentiate between shale-shaly-non shale facies. Shales usually have low density, while non-shale facies has density higher than shale, whereas the shaly facies lies between them. If the facies has a very high density log reading, it may be classified as a "tight" facies, when its gamma ray log reading is around 30-50, it may be regarded as a "tight sandstone" facies or interpreted as anhydrite when the gamma ray log reading is below 15 API, which is considered a good cap rock in petroleum system. A facies with low density usually has high porosity which is needed to store the hydrocarbon fluid. However, for one to effectively optimize the available data, reduce uncertainty and ultimately gain a better understanding of what to expect within the formation, a combination of these logs is recommended. These have also aided the interpretation of environments of deposition of the sediments.

The use of train estimation model can be applied in many aspects of petroleum exploration studies including, paleoenvironmental interpretations (Figure 7), reservoir characterisation and evaluation, ecosystem evolution studies, sequence stratigraphic studies, geophysical and seismological research problems, basin modeling, among others.

Conclusion

Artificial neural networks have shown great potential where inter-relationship between different variables or wireline logs data exist. Lithofacies identification and classification is an important aspect of reservoir characterization study. In the present study attempt has been made to integrate core and well log data to identify and classify lithofacies. This objective has been achieved by invoking the application or the use of Train Estimation Model through artificial neural networks (ANN) algorithms. Such lithofacies characterization is envisaged to be utilized in development of more accurate correlation between permeability and well log data. It is concluded conversely; that the neural network modeling doesn't affect the performance of having lithologic heterogeneities in the reservoir in generation of synthetic logs. Thus, implementation of this technique will reduce the operation costs for oil and gas operators in re-acquiring the necessary wireline logs for interpretation of lithofacies characterization for proper evaluation of the hydrocarbon reservoirs.

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