AAPG Search and Discovery Article #90013©2003 AAPG Annual Meeting, May 11-14, 2003, Salt Lake City, Utah

AAPG Annual Convention
Salt Lake City, Utah
May 11-14, 2003

Application of Neural Networks Technique in Lithofacies Classifications used for 3-D Reservoir Geological Modelling and Exploration Studies. - A Novel Computer-Based Methodology for Depositional Environment Interpretation. (X-Field Example, Niger Delta, Nigeria).

["*The key to Basin-Scale Reservoir Characterisation for the Niger Delta, using Neural Networks*"**]**

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ABSTRACT
In this work, interpreted core data was depth matched to well logs and 8 lithofacies associations were calibrated to define the combined log responses for each genetic unit. These combined log responses were then used to train the supervised neural networks to recognise and interpret these units elsewhere in the case field. Thereafter, the unsupervised neural network was run to classify the cored interval into 7,8 and 9 classes respectively and the results were then compared with the supervised network output. The results were observed to be over 85% accurate. These results were then extrapolated vertically and laterally to other parts of the field.

This technique having been used successfully to perform automatic interpretation of genetic units and lithofacies associations in a reservoir scale can also be very useful in exploration. Data can be extrapolated from a point to a larger area. Specific reservoirs or stratigraphic units can be automatically interpreted across a wide area using interpreted core data. It saves data cost and time. Based on this, computerised Basin-Scale Reservoir Characterisation for the Niger Delta could be achieved incorporating seismic and all other field data.

Introduction:
Artificial neural network is a virtual intelligence tool, which mimics the human brain to do analysis and come out with results. Its application in petroleum engineering is very recent and is gradually evolving and has the potency to dominate or take over other analytical tools used in the Exploration and Production industry.

There are two types of neural network namely, unsupervised and supervised neural networks. The unsupervised network performs classification only, without constraints of interpreted data and is deployed to recognise rock classes elsewhere. The supervised network on the other hand is trained with interpreted data and deployed to perform recognition and interpretation. A proper combination of these two types of neural networks produces results comparable to interpretation done by a human professional.

The main objective of this research and pilot work is to develop a system that will assist in automatic interpretation of depositional environments on the scale of genetic units derived from cores using Neural Networks. Artificial neural network is preferred because of its capabilities to handle complex problems and an operation such as is presented in this work.

Core data is one of the most important data used in reservoir characterisation and modelling. However, because of the high cost of acquiring cores, it is difficult to have the core coverage in as many wells as one would like to have

To achieve the main objective of this work, the logical way forward was to first develop a methodology/technique to capture core interpretation in cored wells and then extrapolate the recognised depositional environments to other un-cored areas of the field in a consistent manner. Artificial neural network in Schlumberger GeoQuest Software, **ROCKCELL*** was adapted for this purpose (Figure 2).

This provides a powerful tool for detailed reservoir characterisation using available cores and log without recourse to expensive acquisition of new data. Also, it is the key to achieving a basin-scale reservoir characterisation for the Niger

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Delta. In addition to this, it provides a user-friendly medium for learning /acquiring core description skills by any geologist using the assistance of Unsupervised Neural Network in RockCell*.

Genetic reservoir units (a combination of lithofacies) are the result of a practical subdivision of a reservoir into components, which have a consistent range of reservoir properties, a consistent external geometry, and electrofacies. Electrofacies refers to groups of rocks that have similar physical properties as measured by petrophysical logging tools by which they can be consistently recognised.

The up-scaling step from lithofacies to genetic reservoir units (micro-to meso-scale) is a key stage in the reservoir geological modelling process. It provides the link, which ensures that the reservoir property data measured from core is properly incorporated into the volume cells (voxels) used in static reservoir modelling and grid blocks in dynamic simulations.

Prediction and measurement of formation characteristics such as porosity, permeability and fluid saturation from conventional Well logs have been done using neural networks (Mohaghegh, 2000).

Supervised neural network
In this paper, description and interpretation from a cored section in the key well was used to train the Supervised neural network.

Having trained the network, it was then used to recognise and interpret the units vertically and laterally in the studied reservoir (Figure 2).

Unsupervised neural network
Genetic units obtained from the conventional reservoir geological core description and interpretation was compared with the classification done by unsupervised neural network in which the network was made to classify the cored interval into the same number of genetic units identified from the cores. A combination of lithology logs was used to subdivide the reservoir intervals into genetic units, lithofacies associations and lithofacies in RockCell*.

By this process of comparing actual interpreted core results with the classes generated by the unsupervised neural network, it serves as a health check for the performance of the supervised neural network. Also a program can be effectively developed to perform neural networks assisted core description and interpretation.

It is also important to have standard-unified log curve codes (as in figure 3) to ease the implementation of this technique in multiple wells. It is also important to have standard-unified lithofacies naming scheme like was used in this work to easily recognise and associate them. These standards will make it easy in accessing the information and applying them in large-scale studies.

Data
Well C1 (Figure 1) was used as the key well in RockCell*. The cored interval comprises 191 ft of recovered cores. Core-log depth matching was carried out. A total of 12 lithofacies, 8 lithofacies associations and 4 genetic units were described and interpreted within this interval (Figure 4a&b).

The described and interpreted core results were divided into Training set and Cross validation set for the purpose of testing the performance of the neural network (Tables 1 & 2).

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Table 1. Training Data Set

Code	**Depth**	Lithofacies Associations/Genetic Unit
7	11399.0-11.409.5	Stratified Channel Heterolith.
6	11409.5-11418.5	Bioturbated Channel Heterolith.
5	11443.3-11449.9	Tidal Channel Sandstone.
4	11463.0-11487.0	Fluvial Channel.
3	11487.0-11508.5	Upper Shoreface Sandstone.
2	11547.5-11559.5	Proximal Lower Shoreface Heterolith.
1	11559.5-11581.5	Distal Lower Shoreface Heterolith.

Table 2. Cross Validation Data Set

Code	**Depth**	Lithofacies Associations/Genetic Unit
7	11399.0-11.409.5	Stratified Channel Heterolith.
6	11409.5-11418.5	Bioturbated Channel Heterolith.
	11418.5-11420	Missing Core
3	11420.0-11427.1	Upper Shoreface Sandstone.
2	11427.1- 11430.5	Proximal Lower Shoreface Heterolith.
1	11430.5-11443.3	Distal Lower Shoreface Heterolith.
5	11443.3-11449.9	Tidal Channel Sandstone.
3	11449.9-11453.7	Upper Shoreface Sandstone.
2	11453.7-11457.3	Proximal Lower Shoreface Heterolith.
1	11457.3-11463.0	Distal Lower Shoreface Heterolith.
4	11463.0-11478.5	Fluvial Channel.
	11478.5-11479.3	Missing Core
4	11479.3-11487.0	Fluvial Channel.
3	11487.0-11508.5	Upper Shoreface Sandstone.
	11508.5-11510.0	Missing Core
2	11510.0-11521.0	Proximal Lower Shoreface Heterolith.
1	11521.0-11524.9	Distal Lower Shoreface Heterolith.
2	11524.9-11535.5	Proximal Lower Shoreface Heterolith.
1	11535.5-11538.5	Distal Lower Shoreface Heterolith.
	11538.5-11539.5	Missing Core
1	11539.5-11547.5	Distal Lower Shoreface Heterolith.
2	11547.5-11559.5	Proximal Lower Shoreface Heterolith.
1	11559.5-11581.5	Distal Lower Shoreface Heterolith.

Procedure

Each lithofacies association from the train set (Table 1, Figure 4a) was used to **train** the neural network following the steps shown in figure 3. The network learns the combination of log responses (GR, SP, CAL, FDC and CNL.) for each unit. After the training, the network was run to recognise and interpret other samples of the lithofacies associations in the cross validation data set (Table 2, Figure 4b) which covers the entire cored interval. This was done to **test** the reliability of the network to reproduce the actual core results.

The network output results were evaluated and the following were considered in order to determine degree of confidence,

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- Compare and contrast actual core Interpretation against Unsupervised and Supervised Neural Network output
- Check boundaries of lithofacies zones
- Does the Unsupervised output make any meaning at unsatisfactory Supervised intervals?
- Test other scenarios with Supervised Network and consider
  – Log quality
  – Number of logs used for training (alternate training logs, e.g. GR+SP, GR+SP+CAL+FDC+CNL, and GR+SP+FDC+CNL+DIPMETER)
  – Depth matching accuracy
  – Deduce information from the unsupervised network output

Once the results were satisfactory, a stratigraphic interval bounded by the same age, exceeding the cored limits was defined and the results were extrapolated vertically in the key (cored) well (Figure 5). Other wells were selected and the network was run again to extrapolate the genetic units laterally still within the defined stratigraphic interval belonging to the same age (Figure 5). The results were later displayed in the strike correlation across the field (Figure 6).

This way while viewing the target reservoir sands in the correlation panel, the details of the intra reservoir units from Neural Networks is also displayed side by side. This is a simpler and faster way of capturing the reservoir characteristics and architecture in a field.

From the lateral extrapolation of results to other wells in the field, the lithofacies associations were correlated between wells. They were observed to vary in thickness from well to well. Also, some disappeared laterally (Figure 6).

3-D setting of depositional environment
The above results are integrated with seismic and other field data to construct a 3-D static geological model.

The lithofacies classifications can also be stored in the database (like FINDER) for other subsurface studies.

Challenge
The neural network output is as good as the data used to train the network. Therefore, the quality of the core description and interpretation, which makes up the training data set, is very important. The depth matching of the interpreted core results to petrophysical log curves is also very vital.

Benefits
The benefits are both for reservoir studies and exploration.

To build a 3-D geological reservoir model, and to effectively capture the intra reservoir geological units or bodies, the intra reservoir units calibrated with core results are extrapolated automatically to other parts of the reservoir under study. And by this the extent and geometry of the units/bodies are determined. Precision is ensured also. In the area of exploration, lithostratigraphic units such as Formations and Members can be calibrated using a Type log in a key well for example and then extrapolated automatically to many other wells in the area (region) under study.

Conclusion
The Neural Networks in RockCell was *used* to learn and interpret rock classes which are equivalent to lithofacies associations and genetic units within the cored intervals using the lithology logs, GR, SP, CAL, FDC and CNL.
The Unsupervised Neural Network calibrations served as a health check and cross validation to enhance the Supervised Neural Network results.

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Based on this study, depositional environments can be interpreted automatically by interpreting core data from a point and extrapolating it vertically and laterally to a larger area guided by geological constraints such as lithostratigraphy, sequence stratigraphy and biostratigraphy.

This technique saves cost and time.

Recommendation
I recommend extensive and wider application of this technique because of the huge untapped potentials.

Acknowledgements
Department of Petroleum Resources (**DPR**)-Nigeria.

The Shell Petroleum Development Company of Nigeria Ltd (**SPDC**).

Schlumberger Information Solutions (**SIS**).

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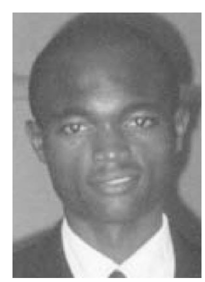
Author Profile
Emeka Iloghalu graduated from Nnamdi Azikiwe University Awka with a B.Sc. in Geological Sciences in 1996. After graduating, did his National Youth Service with Elf Petroleum Nigeria Ltd., where he carried out a Research Project on Review of the Lithostratigraphy of the Tertiary Niger Delta (relevant to STRATCOM). At the end of service year, he went on to do a Masters Degree Program in Petroleum Geology. He joined SPDC for another Research Project to produce a Masters Thesis from where this paper is extracted. He is presently employed by Schlumberger Oilfield Services and is working as a geologist in the Data and Consulting Services (DCS) Segment. He is eager to further contribute to the development of geology applying the most recent technology and to also contribute to better understanding of subsurface geology, especially in the Niger Delta and also in other Deltas around the world.



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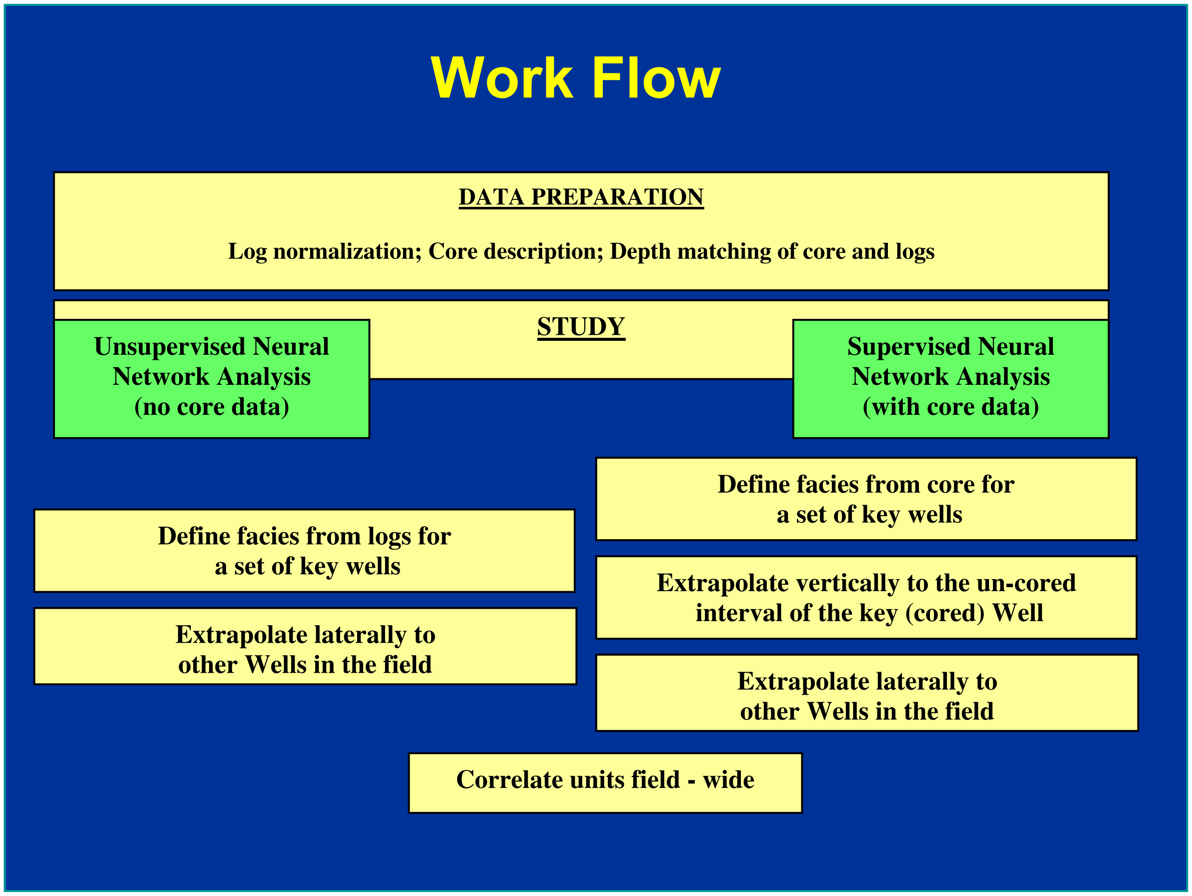

Fig. 1

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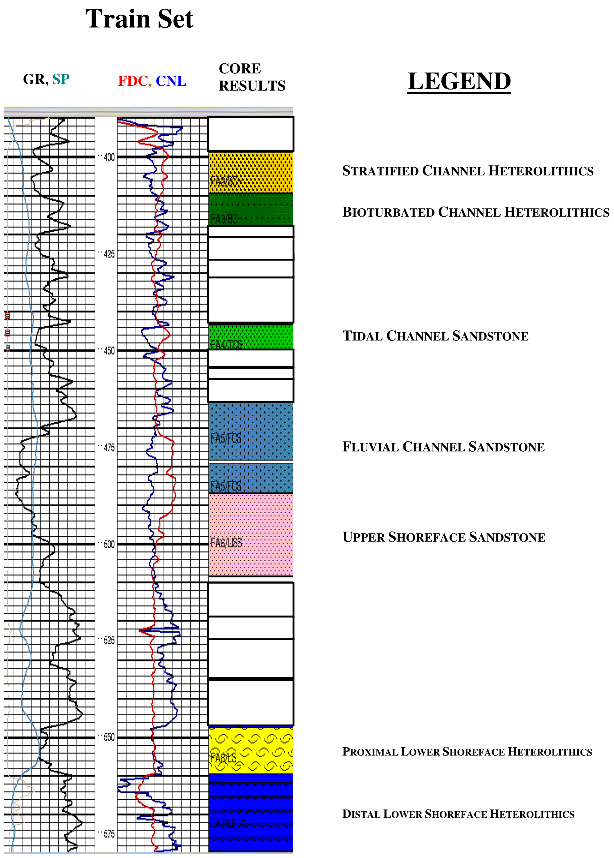

Fig. 4a

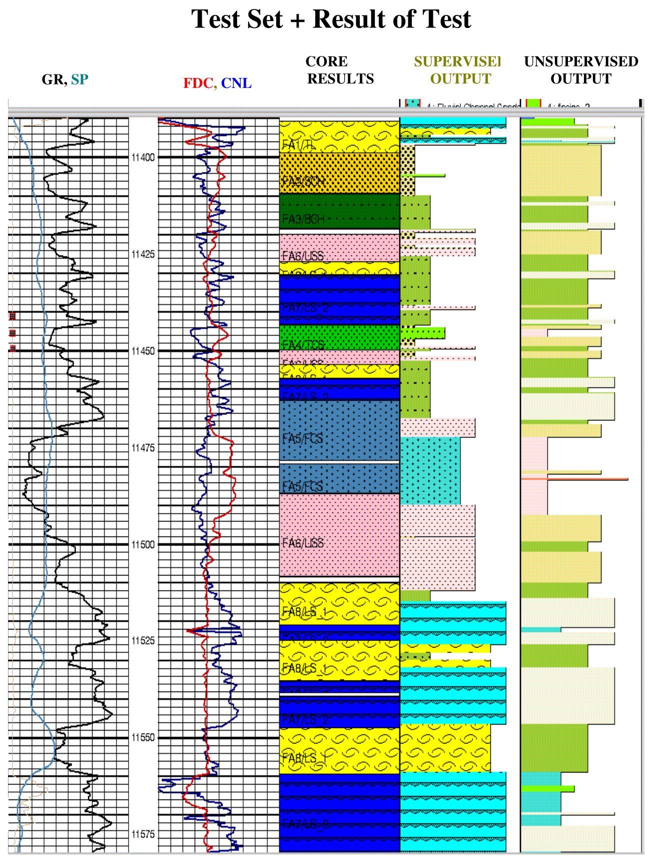

Fig. 4b

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