Porosity Prediction of Unayzah Reservoir in Haradh Field Using Neural Networks.

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ABSTRACT

Unayzah reservoir in Saudi Arabia is a Permian, siliciclastic reservoir and it is the source of light sweet crude oil (Arabian Super light) and sweet gas.

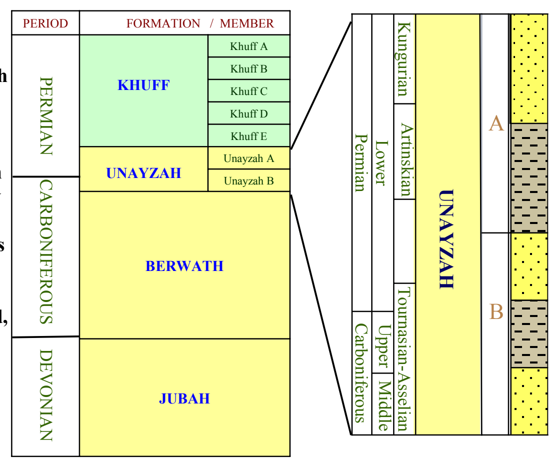
This paper reports the finding of application of Backpropagation Neural Networks for the prediction of porosity values of Unayzah reservoir in Haradh Field, using genetic approach. The usage of genetic approach involves the classification of well logs into various lithofacies groups and then porosity prediction were carried out on facies-by-facies basis. Results from the present study showed that Backpropagation neural networks provides reasonable accuracy and predicted porosity values are highly correlated with the neutron porosity values.

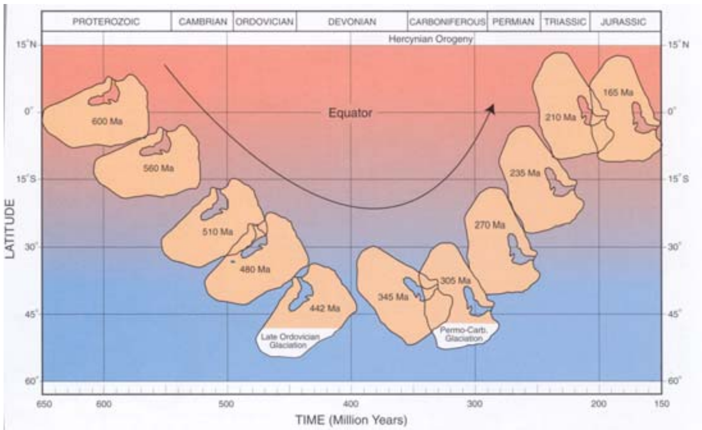
•Unayzah Formation is a thick sequence of dominantly shallow marine clastic sediments deposited on the pre-Unayzah unconformity.

•The formation is underlain by rocks ranging from Precambrian to Devonian age and the formation is unconformably overlain by the interbedded carbonates, shales, marls and channel-fill sandstones of the Khuff Formation.

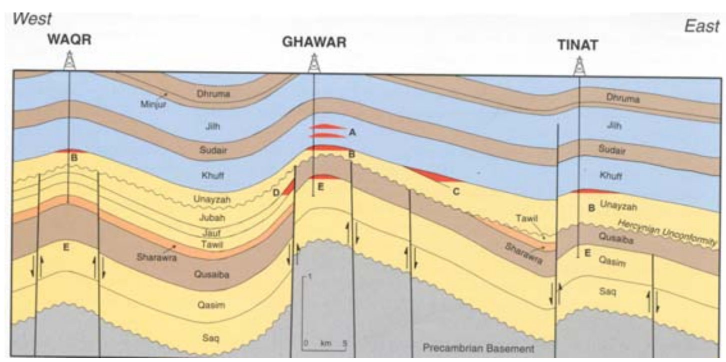
•The Unayzah Formation is wide-spread, covering most of the Great Arabian basin.

•In the subsurface of most part of Arabian basin, the term "Unayzah Formation" is generally applied to the clastic succession deposited between the Hercynian unconformity and the Khuff flooding surface.

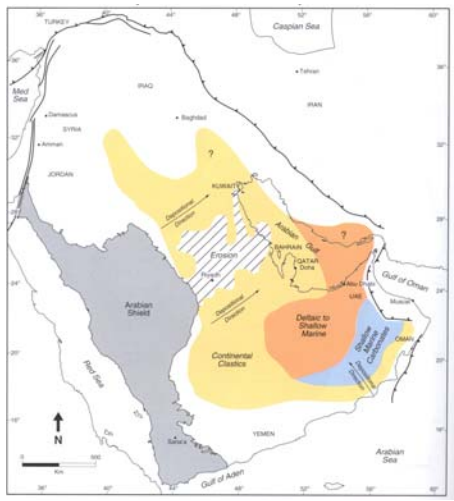




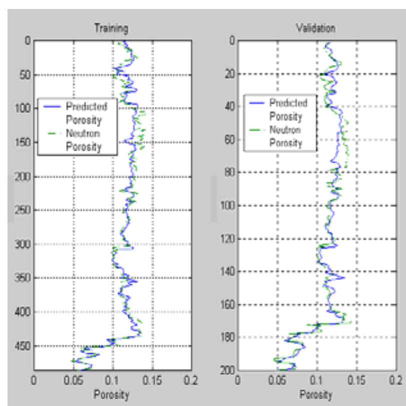
Paleolatitude positions of the Arabian Plate during the Paleozoic.
The Unayzah Formation was deposited between the latitude 30º to 40º south. (source: Ziegler, 2001)



Schematic cross-section across the eastern Saudi Arabian fields including Waqr, Ghawar and Tinat fields. (after Konert et al, 2001)



Early Permian paleofacies map of part of the Arabian Peninsula. In eastern Saudi Arabia, the lower Permian deposits, represented by the Unayzah Formation, are dominantly shallow marine to continental clastics. (after Konert et al., 2001)

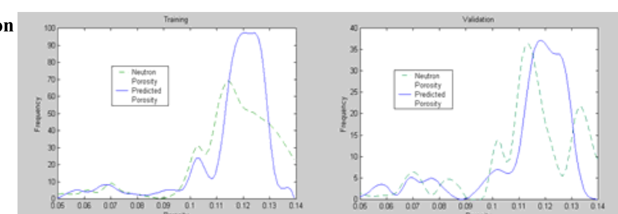


The network was trained in a supervised manner to learn the mapping between the targeted neutron porosity values and the data provided at the input layer. The difference in the actual neural network output and the desired neutron porosity values was used to modify the weights of the neural network using backpropagation algorithm.

•In the training phase, a total of 486 data samples were used iteratively in a random fashion until the results converged to a steady-state Root Mean Square Error (RMSE) value.

•Validation is the process by which the performance of a trained neural network is tested against the data that were not included in the training data set.

•The data used for the validation of the neural network for porosity prediction consisted of 200 randomly selected data samples.

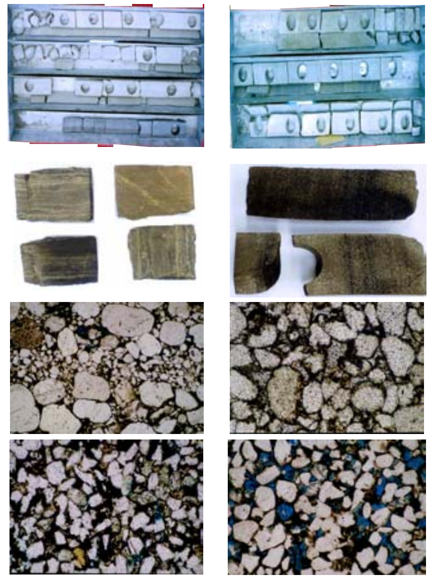


In Haradh Field the Unayzah Formation comprised of sandstones, shale and siltstone.

On the basis of lithology and texture, the Unayzah sandstone in Haradh field can be divided into 2 major lithologic units.

•Unit 1 is identified as quartz wacke. It contains about 5-15 % clay matrix. Texturally, this sandstone is mature to sub-mature. Grain contacts are mostly long and point and the rock fabric is grain-supported.

•Unit 2 is defined as argillaceous wacke. This unit contains about 15-35 % clay matrix and shows microlaminations of alternating coarse and fine sand. On the basis of the texture, this unit can be termed as ``immature". Most of the grain contacts in this unit are point contacts and the rock fabric is matrix-supported as shown by a floating grain fabric.



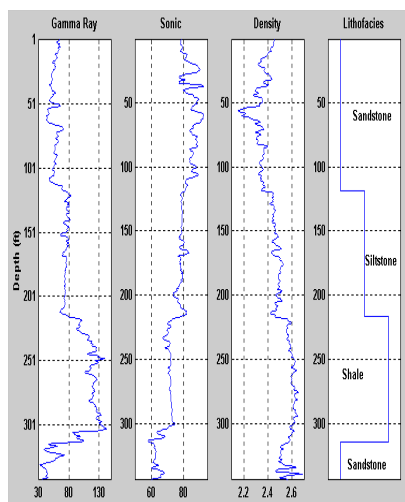
•The genetic approach to reservoir characterization emphasizes the importance of lithofacies in hydraulic properties, such as facies-specific relationship between porosity and permeability.

• Rock types were classified into lithofacies according to similar textural features (grain size and roundness), similar diagenetic histories (mineralogy and pore space changes with time, and similar petrophysical properties (such as porosity and wireline log response).

•The log data set for the studied well include gamma ray (GR), bulk density (RB), sonic travel times (DT), and neutron porosity logs (NPhi).

•Lithofacies information of different lithological units i.e., sandstone, siltstone and shale, obtained from well cores was used.

•Some nonlinear inputs were also generated using RB/DT (i.e., acoustic impedance) or simply IMP and square root values of RB and DT. These nonlinear inputs were constructed for faster and better convergence purposes.



Approach	No of samples	Correlation Coefficient	Mean Absolute Percent Error (%)	Root Mean Square Error (%)
Training	486	0.93	4.38	0.67
Validation	200	0.92	5.10	0.72

Conclusions

•Neural network was successfully implemented for the porosity prediction of Unayzah Reservoir in HARADH Field using well logs data.

•For HRDH-A well, in the training phase the genetic-derived porosity produced a similar distribution to the neutron porosity with a correlation coefficient of 0.93.

•The results of the validation show that the predicted porosity produced a similar distribution to the neutron porosity with a correlation coefficient of 0.92.

References

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Wong, P.M., Gedeon, T. D. and Taggart, I. D, 1995, A Neural Network Approach: IEEE Transaction on Geosciences and Remote Sensing, v. 33, pp. 971-980.