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Advances in Applied Science Research, 2018, 9(2):26-31

ISSN : 0976-8610
CODEN (USA): AASRFC

Artificial Neural Network (ANN) Prediction of Porosity and Water Saturation of Shaly Sandstone Reservoirs

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ABSTRACT

This paper introduces a successful application of neural networks in predicting porosity, fluid saturation and identifying lithofacies using well log data. This technique utilizes the prevailing unknown nonlinear relationship in data between well logs and the reservoir properties, to determine accurately certain petrophysical properties of the reservoir rocks under different compaction conditions. In heterogeneous reservoirs classical methods face problems in determining the relevant petrophysical parameters accurately. Applications of artificial intelligence have recently made this challenge a possible practice. This paper presents successful achievement in applying two trained NN, one for porosity prediction and second training for one for water saturation using 5 log data inputs: (Gamma Ray)GR, (Laterolog Deep)LLD, (density) RHOB, (Neutron) NPHI.

Keywords: Neural network, Porosity, Permeability, Water saturation, Pay zones.

INTRODUCTION

Reservoir characterization and formation evaluation is one of the most important stages in developing oil and gas projects for an accurate and optimal field development strategy. Reservoir characterization and reservoir modeling are processes which need a large range of data such as wireline logs, LWD logs, SCAL data, geological and seismic data. Moreover, an adequate amount of knowledge in underlying physical relationships of all the parameters from these data is also required to integrate them into a conclusion or an interpretation of the reservoir properties. The industry, over the decades, has been using conventional petrophysical methods as a common practice; direct sampling of subsurface fluids followed by a routine analysis in the laboratory and the determination from the well log data using empirical formula and petrophysical relationships. Both mentioned practices are not only expensive and time-consuming processes but also requires relatively high expertise and experience in this field.

Recent advances in petroleum exploration technologies using artificial intelligence and neural networks have granted a new light in the industry for more economical, efficient and accurate reservoir characterization. This does not imply the current common formation evaluation practices are not efficient and accurate enough for practical purposes. These practices such as SCAL and porosity measurement in the laboratory are still a must in early stages of exploration. However, these practices are proven to be having a few drawbacks-the reduced accuracy when the complexity of the reservoir increases; such as shaly sand formations the inability to provide real time predictions for real time decisions while drilling the expensive and time-consuming trait along with the requirement of pure expertise and special equipment.

In this study, the application of neural networks in predicting porosity, water saturation and potential pay zones of shaly sandstone reservoirs will be analyzed, experimented and validated using core data and well log data.

CONVENTIONAL APPROACH

Many forms of heterogeneity in rock properties are present in shaly clastic petroleum reservoirs. Accurate estimation of lithology, porosity and fluid saturation are the key to characterizing reservoir properties and to estimate the volume of hydrocarbons in place to optimize the development and production of a field.

Most of the estimations of key petrophysical parameters like porosity and water saturation can be made by several conventional methods. Conventional petrophysical models emphasize the integration of core data with log data; the adjustment of core data, when required, to reservoir conditions; and the calibration and regression line-fitting of log data to core data. The goal of the petrophysical calculations is to use all available data to get an accurate parameter estimation. Usually, a common log suite is available from the wireline operations; conventional method, the routine-core- analysis data adjusted to reservoir conditions should be used to calibrate the logs for more- accurate calculations at the various wells, [1,2-6].

First, lithology is determined from cores and rock cuttings. This information can be combined with log characteristics to identify depositional environments and how it changes vertically throughout the reservoir using GR log. Volume of shale, usually expressed as Vsh, and is expressed as decimal fraction or percentage, the volume of shale is determined from the shale parameters from the Gamma Ray (GR), formation density neutron porosity, shallow and deep resistivity log data and other reservoir parameters.Porosity then can be computed from a variety of well logs (density, sonic, or neutron) in combination with routine-core data adjusted to reservoir conditions such as clay and heavy minerals need to be identified as part of the lithology determination. Effective porosity values and GR log were evaluated to calculate accurate porosity, the shale content of the formation is determined. The clay minerals that present in the shales and the sandstone intervals must be identified and quantified so that their effects on the logs analysis, selection of the most suitable petrophysical models and routine-core-analysis data can be adequately evaluated.

Lastly, water saturation was computed by the conventional approach using three different independent methods, while estimation of water saturation in shaly sand reservoirs using conventional approach is a complex process since the effect of clay mineral or shale content distorts the direct interpretation of log data in calculating petrophysical parameters using empirical equations. Analyzing shaly sands models; Total Shale Model, (Simandoux, 1963) and effective medium, [1,7,8,13].

INTRODUCTION TO ARTIFICAIAL NEURAL NETWORK

A neural network, firstly introduced in1943, and it is a computational model of a largely distributed processor with parallel networks which use input processing units called neurons to give out a single output value of estimation or determination for non- linear problems. It is a machine-representative of a human brain in a way that it can attain knowledge, store knowledge and learn through a training process to solve for problems with inputs that are unseen before. Just as a human brain is made of nuclei, dendrites and axons to convey signals, the imitated neuronal model is also made of 3 main components; (i) a set of synapses or connecting links each characterized by its "weights" (ii) An adder for combining or generalizing the input signals and (iii) An activating function to limit the boundaries of an output signal [2,5,7,12].

There are different types of activation function from mathematical or algorithmic point of view, namely, Hard limit function (output is either 0 or 1), Linear function (one output value with linear relationship to the input) and Sigmoid function (output varies between 0 and 1). The sigmoid function is proven to be the most suitable for multilayer neural networks as it is trained using back propagation algorithm and has a distinctive non-decreasing behaviour. Neural Networks are developed based on learning algorithms to be trained. A great deal of learning algorithms can be studied but they can be narrowed down and categorized into three main classes

I.Supervised learning; a set of target output is used to train the network by adjusting the weights and biases of the network to get an output that is closer to the target output.

II.Reinforcement learning; No target output is provided, instead, the network is graded for the performance of its algorithm.

III.Unsupervised learning; The weights and biases are adjusted according to the response to the input only using clustering operations.

There are a few types of neural network architecture and concepts developed. However, Multilayer Perceptron architecture with Back Propagation algorithm has been decided to be used in developing the networks for this project, **Figure 1**[9-11].

Back Propagation (BP) Algorithm and Multilayer Perceptron (MLP); uses sigmoid function in the hidden layers

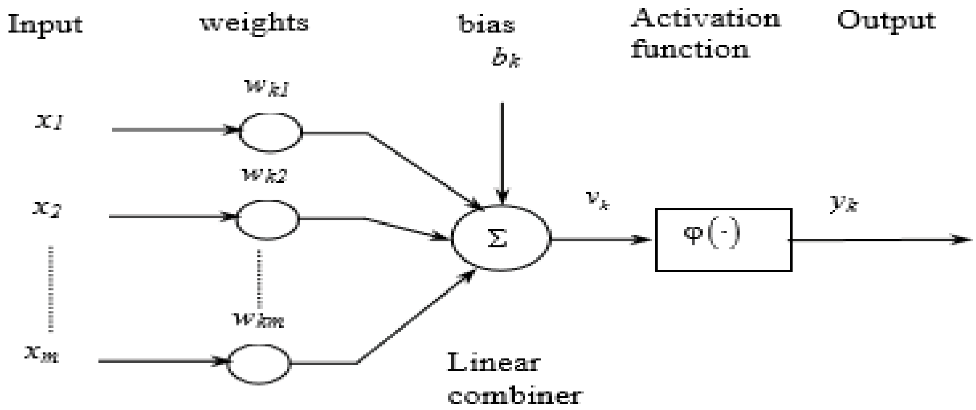


Figure 1: A Neuron Model

and a linear function in the output layer. It is a generalization of LMS algorithm and uses chain rule to calculate the mean squared error with respect to weights and biases. After calculating the derivative of the mean squared error in the last layer, the backward propagation of BP is used to calculate the derivatives of the mean squared error in the hidden layers. It then adjusts its weights and biases and this process is repeated during the training phase. The forward propagation of BP is used only when it is in operation phase.

MLP can provide a non-linear relationship between inputs and outputs. Therefore, the MLP networks are the most suitable for function approximation. The additional advantage is the ability to learn and generalize with its built-in capability to adapt the synaptic weights to decrease the error. Moreover, this network shows great robustness and error tolerance due to its built-in redundancy; even if there are a few faults in its hidden components, the network's overall performance will not be affected.

Unlike Multiple Linear Regression (MLR) which also predicts relationship among variables, MLP does not tend to reinforce the algorithm for predicted values to lie close to the mean values and hence, it maintains the variable and non- linear nature of the data [14-16].

DATA FOR ANN DEVELOPMENT

From this section onwards describes the ANN approach and application in determining three important parameters in hydrocarbon exploration: porosity, water saturation and potential pay zones. A set of logging data of four different wells drilled in Upper Cretaceous shaly sand formation in Western desert, Egypt was available. However, only two sections of two wells from these four had core data available. Core data from well TUT-8 was from the depth 8284 ft to 8373 ft with 90 data points and core data from well TUT-12 was from the depth 8194 ft to 8378 ft with 179 data points. Five types of well log data: Gamma-Ray (GR), Laterolog Deep (LLD), density (RHOB), Neutron (NPHI) and Photoelectric Factor (PEF), for developing of petrophysical properties by the neural network approach will be presented. Porosity and water saturation for TUT-8 & TUT-12 were predicted by the neural network approach. The results were plotted against depth in comparison with the core data and conventional method.

The available data was allocated to three sets which were training, validation and testing: 70%, 15% and 15% respectively. The training algorithm used in this project was Levenberg-Marquardt as this algorithm is easy to understand mathematics-wise and training is time-efficient, especially in data fitting and function approximation problems. A variety of network structures were tested by trial and error to select the ones with best accuracy.

HYDROCARBON PAY ZONE ESTIMATION BY ANN APPROACH

Potential hydrocarbon pay zones were estimated using log data by setting cut-off values of shale volume, porosity and water saturation. Any section of the well which satisfied the following criteria was considered to be a hydrocarbon pay zone.

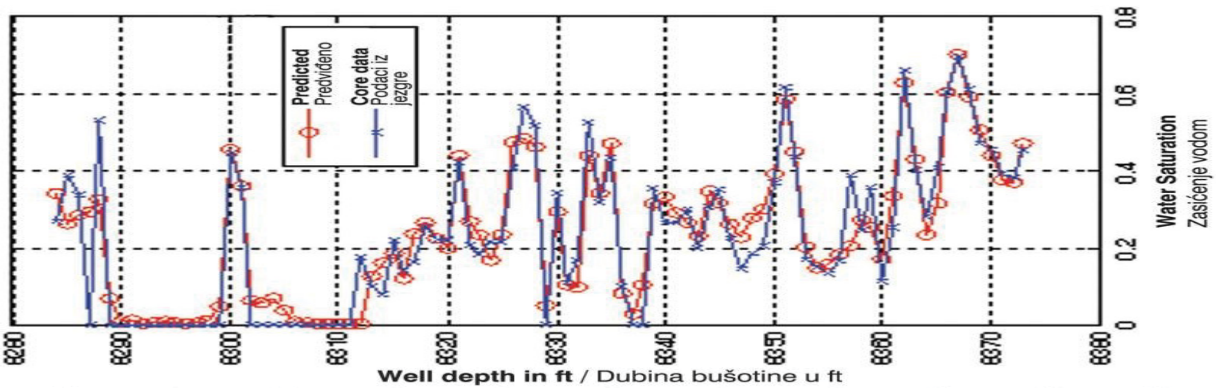
First, the above three parameters for cut-off consideration were calculated where porosity and water saturation were estimated by ANN approach. Comparison of the results from ANN approach with the core data can be observed in the following sections in **Figures 2 and 3**.

NEURAL NETWORK APPROACH

The NN developed for porosity estimation uses six log data input: GR, LLD, RHOB, NPHI, PEF and Δt. It consists of two hidden layers with one output layer. The two hidden layers consist of 25 and 12 neurons each, applying tan-sigmoid function where the output applies log-sigmoid function. The NN achieved Mean Squared Error (MSE) of 0.001412 with training data and 0.00154 with validation data. The ANN predicted porosity showed a good match with the core data as seen in **Figure 4**.

The NN developed for estimation of water saturation also consists of two hidden layers with 16 and 5 neurons each and uses 5 data inputs: GR, LLD, RHOB, NPHI, and PEF. The NN achieved MSE of 0.0109 with training data and 0.012 with validation data. The match of ANN water saturation with the core data can be seen below in **Figure 2**.

Finally, the ANN predicted results were used to determine potential pay zones using cut off values of shale volume, porosity and water saturation and the result can be seen in Figure 4, showing threshhold value of 0.70 (70%). The total payzone was shown to be about 9% which is 28 fth of the 320.5 ft section of the well TUT-8.



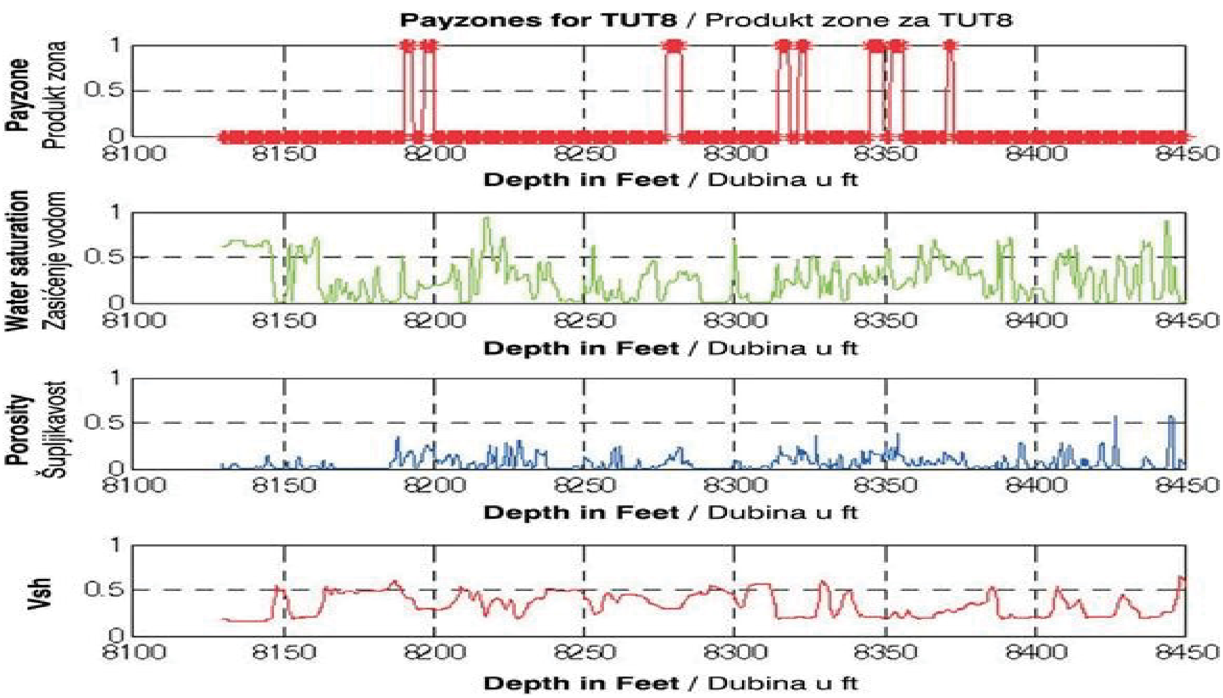


Figure 3: Shale Volume, Porosity, Water Saturation and Pay Zones

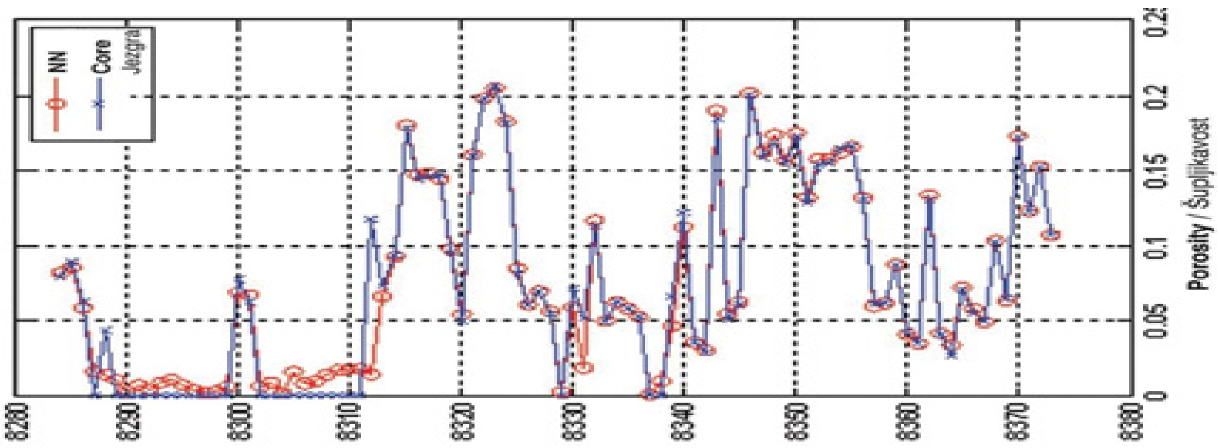


Figure 4: ANN Predicted Porosity, Core Porosity vs depth

CONCLUSION

In summary, two ANN were successfully developed, one for porosity estimation and one for water saturation estimation. Based on the results, both ANN showed a good match with core data and acceptable mean squared error when validated. The potential hydrocarbon pay zones were accurately predicted using ANN estimated values of porosity and water saturation cut-offs. This study aimed to be a part in building accurate and effective modern formation evaluation techniques using ANN. More studies with different networks on different field data is recommended for additional evidences of the successful of ANN application in petro physical evaluation.

REFERENCES

[1] Archie GE. The Electrical Resistivity Log as an Aid in Determining Some Reservoir Characteristics. *Trans. AIME,* **1942,** 146:54-62.

[2] Bhatt A, Helle HB, Ursin B. Application of parallel neural networks in reservoir characterisation from well logs. *EAGE/SEG Research Workshop on Reservoir Rocks,* **2010.**

[3] Understanding reservoir rock and fluid property distributions - measurement, modelling and applications.

[4] Dresser Atlas. Well Logging and Interpretation Techniques. *Dresser Atlas Indus,* **1982**.

[5] Fertl WH. Shaly Sand Analysis in Development Wells. Paper A Presented at SPWLA Annual Conference, USA **1975**.

[6] Hagan MT, Menhaj M. Training Feed Forward Networks with the Marquardt Algorithm. *IEEE Transaction on Neural Networks,* **1994,** 5:989-993.

[7] Hamada GM. Quality Assurance Lessens Core, Log Data Uncertainties. *Oil & Gas Jr,* **2006,** 41-46.

[8] Haykin S. Neural Networks; A Comprehensive Foundation, Macmillan Publishing Company Englewood Cliffs. **1994.**

[9] Helander DP. Fundamentals of Formation Evaluation. *OGCI Publication,* **1983**.

[10]Hornik K, Stinchcombe M, White H. Multilayer feed-forward network are universal approximations. *Neural Networks,* **1989,** 2:359-366.

[11] Ketineni SP, Ertekin T, Anbarci K, Sneed T. Structuring an Integrative Approach for Field Development Planning Using Artificial Intelligence and its Application to an Offshore Oilfield. *Society of Petroleum Engineers,* **2015**.

[12] Kohli A, Arora P. Application of Artificial Neural Networks for Well Logs. *International Petroleum Technology Conference,* **2014**.

[13] Malvic T. Clastic Facies Prediction Using Neural Network (Case Study from Okoli Field), Nafta. **2006,** 56:415-431.

[14]Panes R, Quaglia A. Reserves Re-Estimation Using Scal to Validate Sw Model from Neural Net Processed Oil Logs. La Ceibita Field, Eastern Venezuela, Case Study. SCA # 47 Paper presented at SCA Annual Symposium, Norway. **2002**.

[15] Powell MJD. Restart Procedures for the Conjugate Gradient Method. *Mathematical Programming,* **1997,**12:241-254.

[16]Riedmiller M, Braun H. A Direct Adaptive Method for Faster Back propagation: The RPROP algorithm," presented at Proceeding of the IEEE International Conference on Neural Networks. **1993**.

[17]Rosenblatt F. The Peceptron: A Probabilistic Model for Information Storage and Organization in the Brain. *Psychological Review,***1958,** 65: 386-408.