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Porosity Prediction from Wireline Logs Using Artificial Neural Networks: a Case Study in north-east of Iran

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Abstract

The objective of this study is a modeling in artificial neural networks (ANN) and its generalization to predict reliable porosity values from log data obtained from three wells in Khangiran gas field located in north-east of Iran. We used a back-propagation ANN method (BP-ANN) to predict porosity. The ANN for porosity is a simple three-layer network which uses sonic, density and resistivity logs for input. Porosity predictions were then compared with log porosity which had been derived from density and neutron logs. The results confirmed the capability of using ANN.

Keywords: *porosity, artificial neural network, wireline logs, Khangiran, Mozduran.*

Introduction

Initially, electric logs were used mostly for the determination of formation tops and bottoms, and also for determining the oil-water contact. Later, electric logs were used to evaluate most of the reservoir properties such as porosity, permeability, fluid saturation, temperature, reservoir pressures, type of formation and mineral identification. Several studies imply that accurate evaluation of reservoir properties can be made by analysis of electric logs (Hearst, 2000; Al-Qahtani, 2000; Helle et al., 2001). Characterizing a reservoir is a very complex task, due to its inherent heterogeneity. Heterogeneous reservoirs are known for the variation in their properties within a small area. Distinct geological ages, nature of rock, depositional environments are some of the reasons behind the heterogeneity of a formation.

Artificial neural networks (ANN) are one of the latest technologies available to the petroleum industry (Poulton, 2001). Porosity is a key variable in characterizing a reservoir. Several relationships have been offered which can relate porosity to wireline readings, such as sonic transit time and density logs. However, the conversion from density and transit time to equivalent porosity values is not trivial (Hearst, 2000). We developed a network for prediction of porosity in Khangiran gas field in north-east of Iran in a similar approach to that of Helle et al. (2001). Mozduran formation (upper Jurassic carbonates) is the most important pay zone in Khangiran anticline. Mozduran formation contians three members. Upper and middle members of this formation are dolomity and limydolomity types, respectively and lower member is dolomylimstone (NIOC, Well completion report). The read data of logs for Mozduran formation from three wells (KH#35, 36, 46) in this field were selected for case study. At first, we studied the essence of neural networks and tried to write program for back-propagation algorithm for porosity network. Then, we trained this network with wireline data and adjusted its parameters. Also, generalization of porosity network was done for every well.

The Log Conversion

Porosity is one of the fundamental properties of reservoir rocks and it is the measure of the void space in a rock (Hearst, 2000). Porosity normally obtained either with wireline logs or by direct measurements on core samples. Coring is one of the oldest and still practiced technique. However, coring every well in a large field is a time consuming practice and can be very expensive. Geophysical logs are available for most of the wells, while cores and tests are available from few wells in the reservoir. Therefore, the evaluation of porosity from well log data is an important step to minimize cost (Hearst, 2000). In this case study, sampling in Khangiran 35, 36, and 46 wells has been done only for lithological studies and there isn't any core for them (NIOC, Well completion report). Better estimation of the porosity can be obtained when the latest technology available is applied. The density and sonic logs do not directly measure the parameter with which it has become associated, i.e. the porosity. From density and sonic logs the porosities are given respectively, by

$$\phi_\rho = \frac{\rho_m - \rho}{\rho_m - \rho_f}, \qquad (1)$$

and

$$\phi_{\Delta t} = \frac{\Delta t_m - \Delta t}{\Delta t_m - \Delta t_f}, \qquad (2)$$

where ρ_m, ρ_f and ρ are the matrix density, fluid density and bulk density, respectively. Δt_m, Δt_f and Δt are the sonic transit times of the matrix material, the pore fluid and the rock, respectively (Wyllie, Gregory and Gardner, 1956).

A single log cannot by itself resolve a petrophysical property (Helle *et al.*, 2001). Alternatively, a suite of different logs in combination may be used to quantify a given petrophysical property provided its relationship to the log readings can be established. Except for the unknown values of the grain material and fluid properties, the porosity can be expressed by linear functions of bulk density (equation 1) and sonic transit time (equation 2). Because the sonic and density logs respond differently to the fluid and grain material, and since they constitute independent measurements of the same property, a combination of two may improve the accuracy compared with that of the log-to-porosity transform based on sonic or density alone. Moreover, by adding the resistivity to suite of the logs, the accuracy of the porosity transform may be further improved since resisitivity is normally the best indicator for the type of pore fluid. In the following sections we demonstrate that the sonic, density and resistivity combined into an artificial neural network provide accurate porosity estimations for any combination of grain material and pure fluid.

In this case study, for training of the porosity network we selected the target porosity (ϕ_{tar}) from the combined density (ϕ_D) and neutron (ϕ_N) porosities as following:

$$\phi_{tar} = \left(\frac{(\phi_D)^2 + (\phi_N)^2}{2} \right)^{1/2}, \quad (3)$$

In this case study, based on drilling reports in Mozduran formation, hydrocarbon effects have been considered as gas and condensate (liquid gas) in KH#35 well. The KH#36 well contains gas and brine but KH#46 well contains only brine (NIOC, Well completion report). We calculated log porosity for every well in the pay zone (Mozduran formation) using a constant matrix density of 2.85 g/cm^3 (i.e. limydolomite) and with different fluid densities of 0.25 and 0.75 and 1.03 g/cm^3 for gas, oil and brine, respectively and then we compared their responses together (figure 1). As can be seen from figure (1), the comparison between porosity curves for different situations of brine, oil and gas saturation shows that the porosity curve for oil saturation lies between two other curves. Because of the gas effect on the estimated porosities of two logs and the presence of brine and condensate in the reservoir, we selected the target porosity from the curve obtained by oil saturation which its density is compatible with the condensate density.

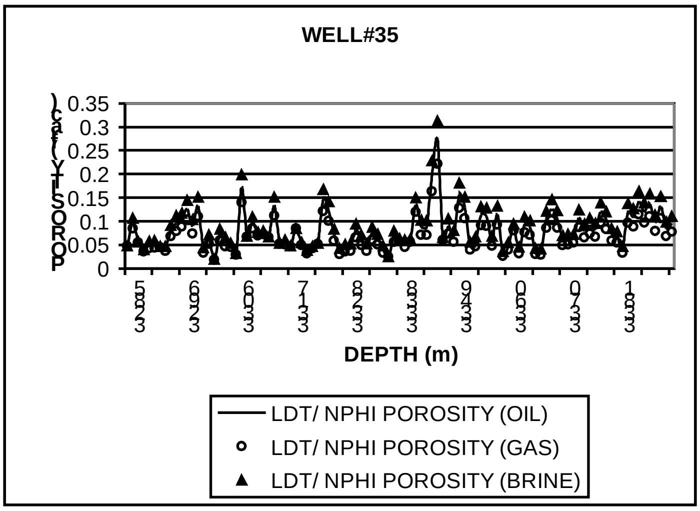

Figure 1 - Comparison LDT/ NPHI log porosity for gas and oil and brine saturation [KH#35].

Back-Propagation Neural Networks

The back–propagation artificial neural network (BP-ANN) is a relatively new tool in petroleum geoscience, which is gradually being introduced into several practical applications including seismic analysis (Poulton, 2001). It simulates the cognitive process of the human brain and is well suited for solving difficult problems, such as character recognition, which are not amenable to conventional numerical methods (Helle et al., 2001). The ANN functions as a non-linear dynamic system that learns to recognize patterns through training. The network has two major components (Callan, 1999): nodes or neurons and connections, which are, weighted links between the neurons (figure 2).

Upon exposure to training examples (patterns), the neurons in an ANN compute the activation values and transmit these values to each other in a manner that depends on the learning algorithm being used. The learning process of the BP-ANN involves sending the input values forward through the network, and then computing the difference between the calculated output and the corresponding desired output from the training data set. This error information is propagated backwards through the ANN and the weights are adjusted. After a number of iterations the training stops when the calculated output values best approximate the desired values (Callan, 1999). The similarities between BP-ANN and the common geophysical inversion techniques are obvious. The ANN approach has several advantages over conventional statistical and deterministic approaches. The most important one is that it is free from the constraints of a certain function form (Helle et al., 2001). There are two questions in neural network design that have no precise answer because they are application-dependent:

1 How much data do we need to train the network?

2 What is the best number of hidden neurons to use?

In general, the more facts and the fewer hidden neurons there are, the better (Callan, 1999). There is, however, a subtle relationship between the number of the facts and the number of hidden neurons. Too few facts or too many hidden neurons can cause the network to memorize, implying that it performs well during training, but tests poorly and fails to generalize. There are no rigorous rules to guide the choice of the number of hidden layers and the number of neurons in the hidden layers. However, more layers are not better than few, and it is generally known that a network containing few hidden neurons generalizes better than one with many neurons (Helle et al., 2001). In this case study, at first we chose twelve neurons for hidden layer of porosity network and then decreased the number of neurons one by one to seven and we found that ten neurons gives the best condition. The standard back-propagation algorithm has been given in different handbooks about neural (Callan, 1999).

The Porosity Network

For the porosity network we used the architecture shown in figure (2) with three neurons in the input layer, i.e. density (Litho Density Tool: LDT), sonic (Bore Hole Compensate: BHC) and resistivity (Latero Log Deep: LLD). A single hidden layer has ten neurons and the output layer has only one neuron (porosity). The mian advantage of using porosity derived from the density measurements is the fact that these are the best possible estimates of in situ porosity values since the compressibility of the pure grain material is likely to be small compared with that of the matrix (Lucas, 1998). The grain density in the laboratory is thus not very different from in situ values, and hence the porosity estimates are less prone to pressure corrections than those based on core plug.

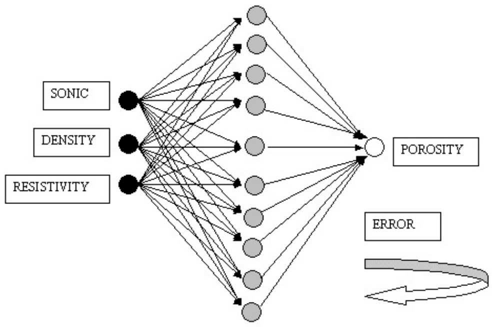

Figure 2- Architecture of a BP-ANN with three nodes in input layer, ten nodes in hidden layer and only one node in output layer.

Initially, for the porosity network, we selected and sorted data from three wells in Khangiran Gas Field in northeast of Iran only for pay zone (Mozduran formation) for training, testing and validation of network separately and then we generalized this network for every well and adjusted the parameters of this network with trial and error. Also, we composed the log data of three wells together and did the above steps for this synthetic well. For the verification of the network, two sets of data are used during training, which are completely separate: a set of training patterns and a set of training-testing patterns. Weight adjustments are based on the training patterns, however, at intervals during training, the error is computed and the net is saved on the best performance on the test set. When the error begins to increase, the net starts to memorize the training patterns too specifically and starts to lose its ability to generalize as well. At this point, the training should be concluded (Callan, 1999). Calibration is another useful parameter when training a net; since it defines how often the test set is evaluated, thus optimizing the network's generalization (Al-Qahtani, 2000). Other way to verify the network's predictions is by using a third data set called the production set, which is not used in the training process of the net. In this study, verification was performed by use of training set, testing set (training-testing set) and validation set (production set). The production set contains similar data to that of the training and test patterns, that is, a set of inputs describing features as well as its correspondent target outputs. This data set is rather utilized to compare the predictions of the network with the actual target values by exposing the developed to that set (Callan, 1999).

Figure 3 shows the trend of training of the porosity network. With the learning rate of 0.7 the initial network converges to sum square error (SSE) of 0.001. Therefore, at this stage more attempts should be done to generalize the network. We compared the porosity predicted by ANN with those predicted by the density-neutron porosity transform (equation 3). Figure (4), shows the best linear fit and regression between ANN porosity and log porosity and figure (5) shows the comparison between the two values for well No. 35. Also, figures (6) and (7) and figures (8) and (9) show the similar cases for wells Nos. 36 and 46, respectively. For composition of these three wells, figures (10) and (11) show the regression and comparison between ANN porosity and log porosity. As can be observed from figures (4) to (11), the ANN method is a reliable tool for estimating porosity from well log data.

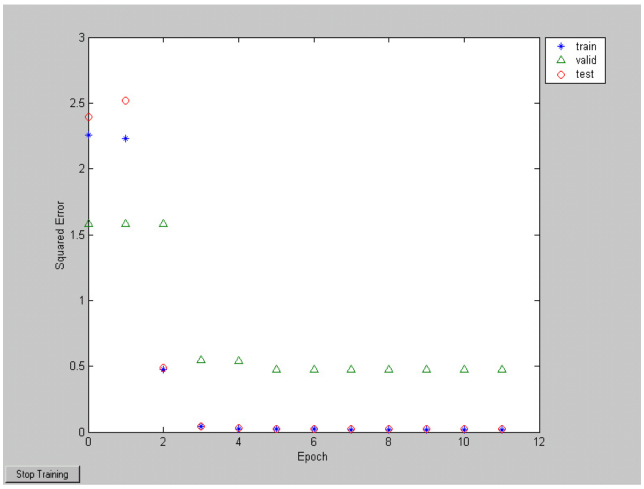

Figure 3 - Squared error versus epoch for training and testing and validation with learning rate of 0.7 for initial network [KH#35].

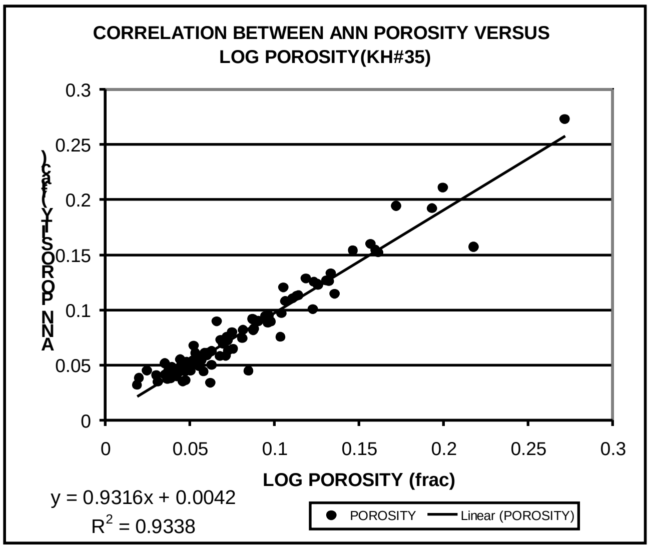

Figure 4 - Correlation between ANN porosity versus log porosity for well KH#35.

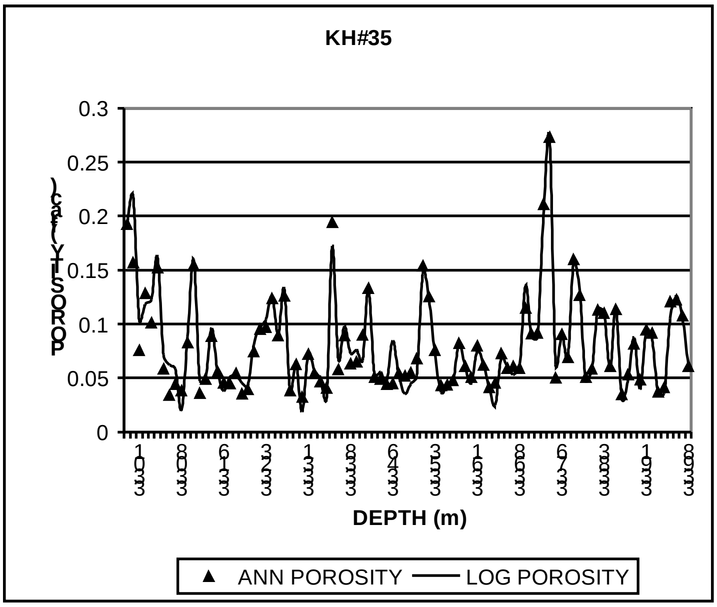

Figure 5 - Comparison ANN porosity with log porosity for well KH#35.

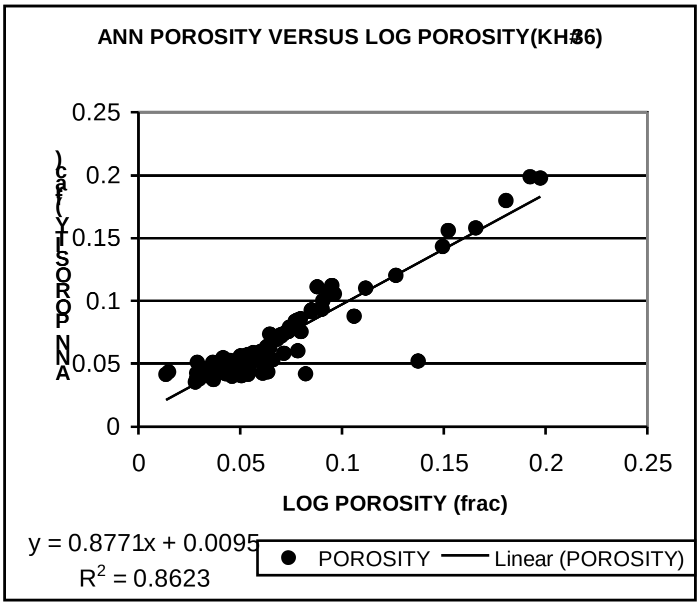

Figure 6 - Correlation between ANN porosity versus log porosity for well KH#36.

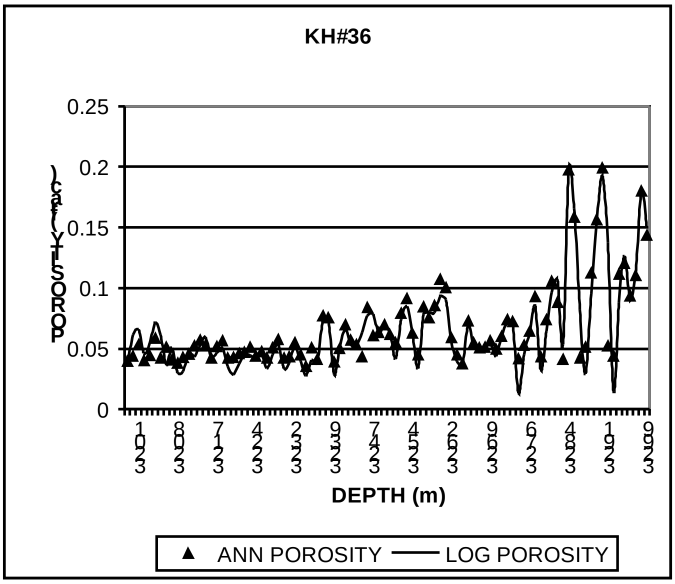

Figure 7 - Comparison ANN porosity with log porosity for well KH#36.

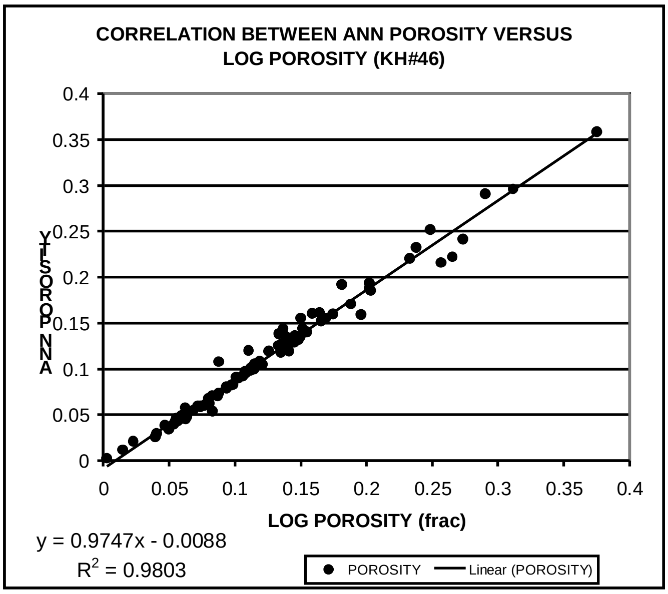

Figure 8 - Correlation between ANN porosity versus log porosity for well KH#46.

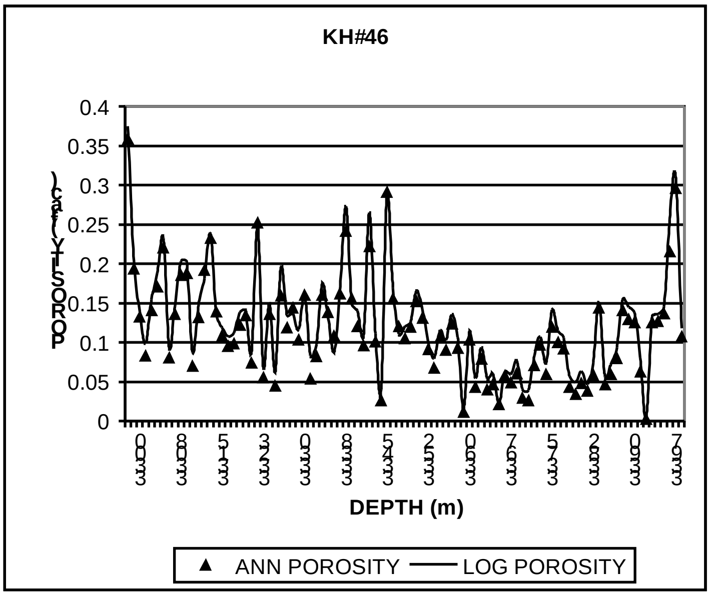

Figure 9 - Comparison ANN porosity with log porosity for well KH#46.

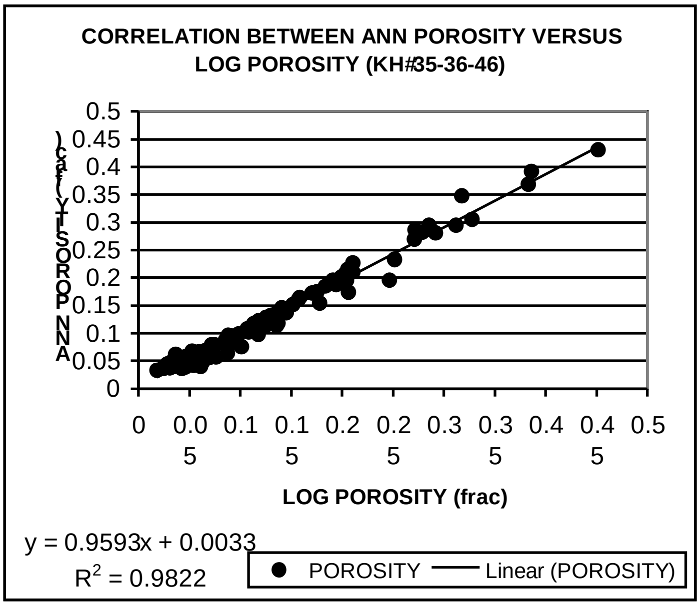

Figure 10 - Correlation between ANN porosity versus log porosity for combined data of three wells.

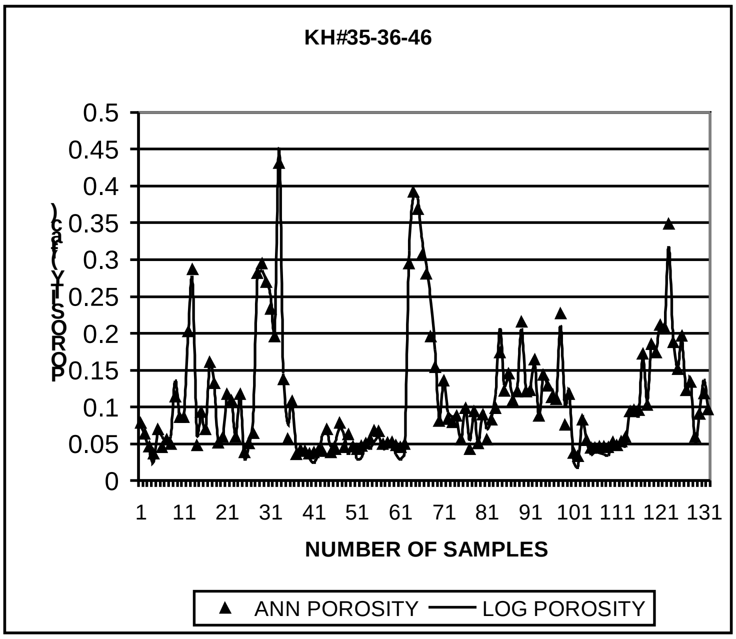

Figure 11 - Comparison ANN porosity with log porosity for combined data of three wells.

Conclusions

The neural net approach requires no underlying mathematical model and no assumption of linearity among the variables. The main drawback of the method is the amount of effort required to select a representative collection of training facts, which is common for all models relying on real data, and the time to train and test the network. On the other hand, once established the application of the network requires a minimum of computing time. The network approach, also, requires no a priori knowledge of the matrix material and pore fluid, and can thus equally well be applied while drilling without prior petrophysical evaluation. Our porosity predictions obtained from ANN method are sufficiently accurate in comparison to that obtained from the density log data.

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