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Estimation of Reservoirs Fracture Network Properties Using an Artificial Intelligence Technique

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Abstract

The main objective of this study is to develop a subsurface fracture map of naturally fractured reservoirs by overcoming the limitations associated with different data sources in characterizing fracture properties. Some of these limitations are overcome by employing a nested neuro-stochastic technique to establish inter-relationship between different data, as conventional well logs, borehole images (FMI) and seismic attributes etc. and then characterise fracture properties in terms of fracture intensity for each data source.

Fracture density is an important property of a system of fracture network as it is a measure of the cumulative area of all the fractures in a unit volume of a fracture network system. At the wellbore locations, fracture intensity and fractal dimension can only be estimated for limited sections where FMI data are available. Therefore, artificial intelligence technique is applied to approximate the quantities at locations along the wellbore, where the hard data is not available.

Keywords: Fracture intensity; Neural Network

INTRODUCTION

Simulation of fluid flow and production potential evaluation of naturally fractured reservoirs require a flow model and generated subsurface fracture map using fracture intensity and fractal dimension in the reservoir blocks (Abdel Azim, 2016 and Abdel Azim et al. 2016). Therefore, this paper presents an integrated methodology to develop a subsurface fracture map for naturally fractured reservoirs by overcoming the limitations of different data sources in characterizing fracture properties. In our methodology, the artificial intelligence technique has been employed to overcome these limitations by establishing inter-relationship between different reservoir data. The available data sources which have been integrated into the developed neuro-stochastic fracture mapping technique include Formation Micro Images (FMI), core descriptions, and conventional well logs.

The subsurface fracture map is generated using two main steps in the presented methodology: (1) the fracture intensity value obtained using FMI log at certain well locations used to establish a correlation between the fracture intensity and the conventional well logs by using the artificial intelligence technique, then this correlation is utilized to generate the continuum map of fracture intensity along the wellbores (2) the obtained continuum map of fracture intensity at wellbores is used to generate the spatial 3D map of fracture intensity using artificial intelligence at locations along the wellbore where the hard data is not available. At the wellbore locations, fracture intensity can only be estimated for limited sections where FMI data are available. The artificial intelligence technique finds a complex relationship between a set of data through an iterative training process (Dombi et al. 2012).

Different conventional well logs, such as DEPTH, GR, NPHI, RHOZ, CAL, PEFZ, RLA1 and RLA5 (see Fig.1 (a and b)) are used to find correlations between them and fracture density and fractal dimension values obtained from well bore images and core descriptions. The obtained correlations are then used to estimate the continuous map of fracture intensity along each wellbore section.

As can be seen from Fig.1 that the minimum and maximum values for GR, RLA1, RLA5, NPHI, and RHOZ are ranging from 20-350 API, 1- 400 ohm.m, 1- 900 ohm.m, 0-0.4, and 2.4-3 respectively.

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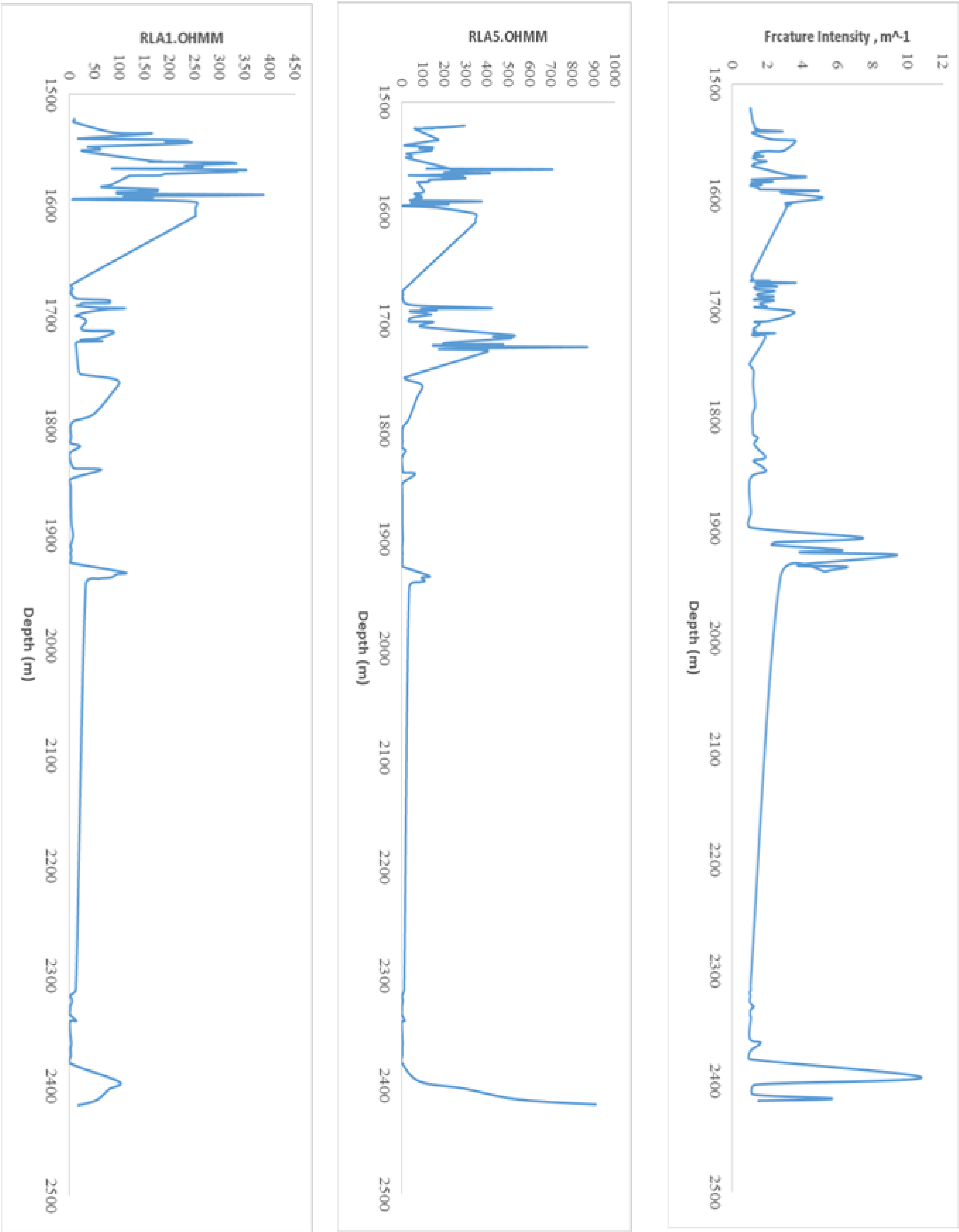

Figure 1: Conventional well logs data (a).

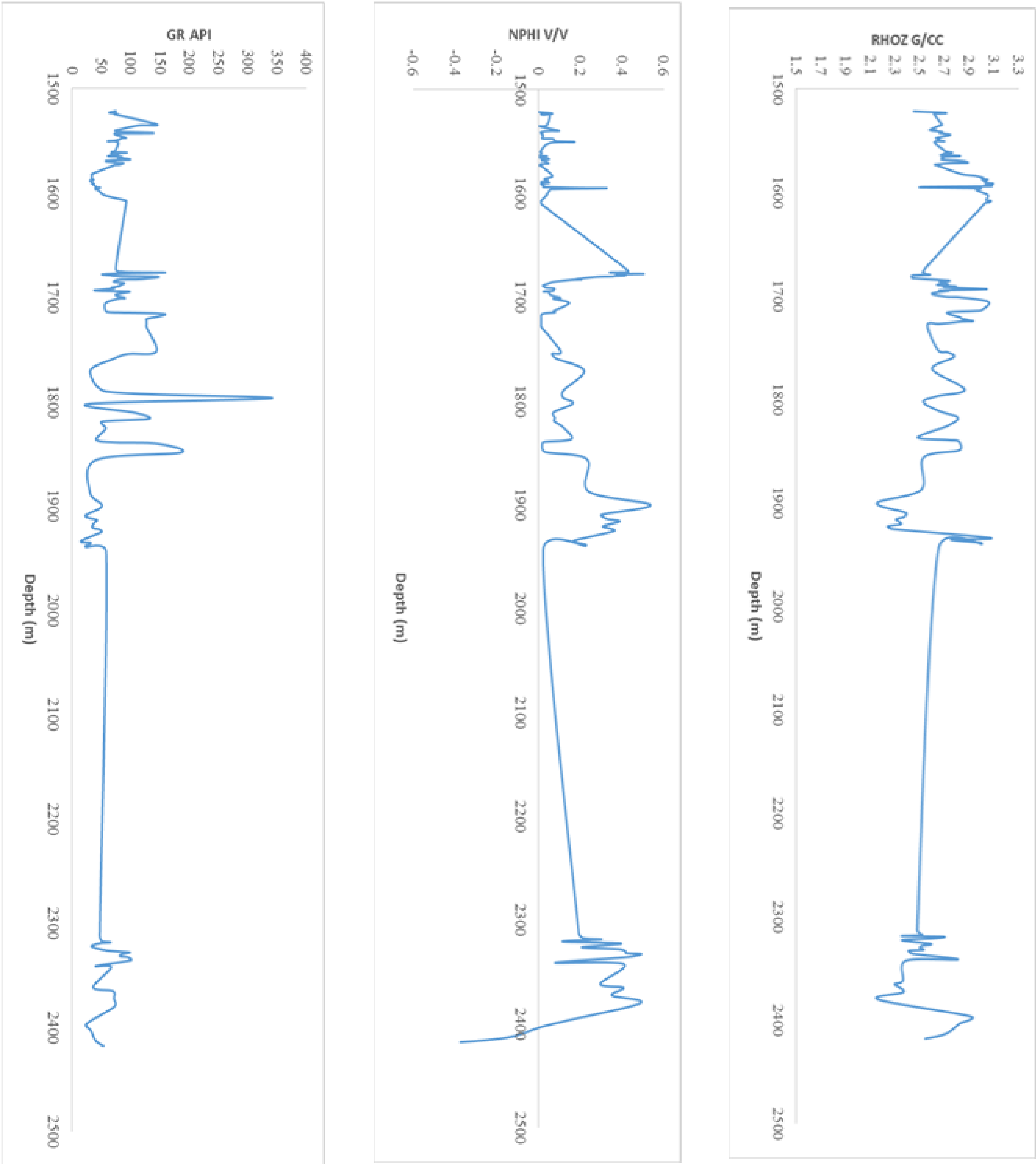

Figure 1: Conventional well logs data (b).

SYSTEM DEVELOPMENT

To develop a fracture intensity required to generate subsurface fracture map for naturally fractured reservoirs, a neural network (NN) based system is proposed. NNs are tools that mimic human brains. They have so many paradigms, among which is Back-Propagation, which has proven its effectiveness in many engineering applications (Lavrenz et al. 2017; Mantha et al. 2017; Das 2016; Huang 2010; Shehab and Farooq 2013; Shehab and Meisami 2013; Shehab et al. 2010; Wilmot and Mei 2005; Khan et al. 1999; Kim et al. 2005). Back-Propagation neural networks consist of an input layer, output layer and, at least, one hidden layer (Figure 2). As depicted in Figure 2, each layer consists of one or more neurons (e.g. N_{i1}). These neurons are linked to each other using weighted connections (e.g. W_{i1h1}), which represent the network state of knowledge.

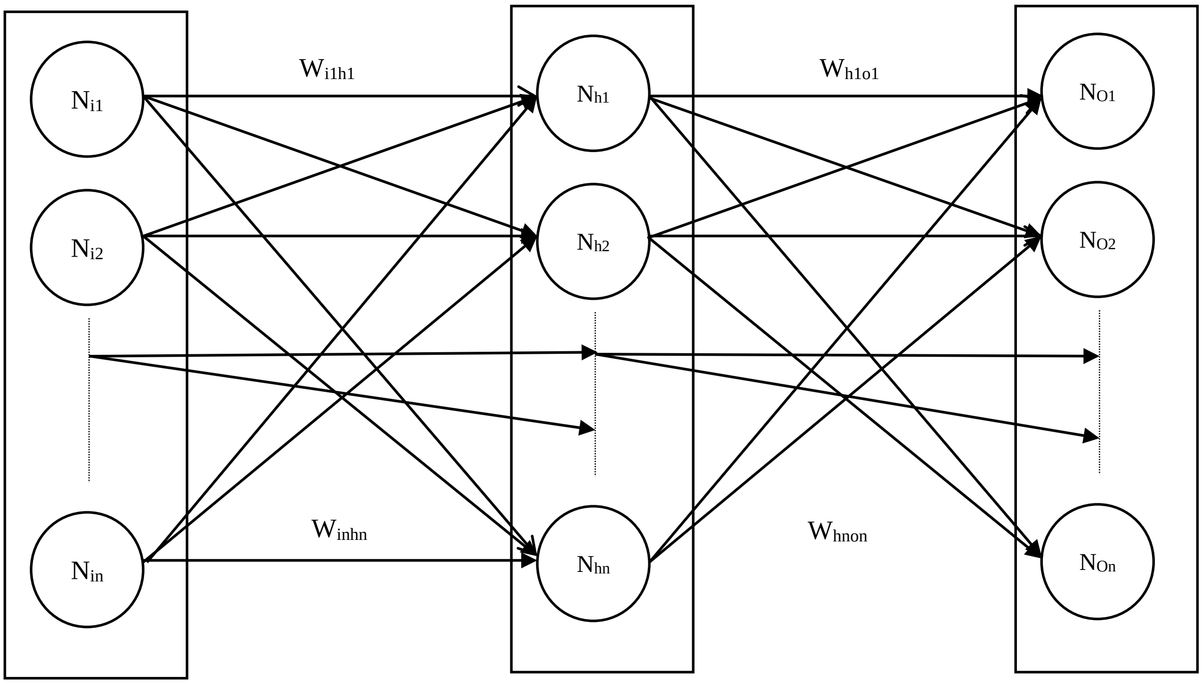

Figure 2: Generic Back-Propagation Neural Network Structure.

To design the Back-Propagation neural network, the number of neurons in each layer needs to be determined. In so doing, the number of neurons in the input and output layers must be associated with the number of input attributes and output results, respectively. Although the number of neurons in the input and output layers are very easy to be defined, determination of the number of neurons in the hidden layer is challenging. This is mainly attributed to the lengthy trial and error procedure involved in this process. What adds to the complicated process of designing Back-Propagation neural networks is selection of learning rates and momentum, which are required for training purposes. It should be noted that while the learning rate impacts the amount of weight modification during the training process, the momentum factor determines the proportion of the last weight change that is added into the new weight change (NeuroShell-2 2008).

To train Back-Propagation neural networks, a supervised technique is implemented. In so doing, the network is exposed to a set of inputs associated with their actual outputs. During this exposure, the network implements its training algorithm to process each set of input and calculate their output. These calculated outputs are then compared to the actual ones, and the differences are further processed to be reduced. This comparison process is usually repeated for hundreds of times, until the difference between the calculated and actual outcomes can not be substantially reduced, at which time the training process is terminated and the weight associated with all neurons' links are saved. The detailed training process of Back-Propagation neural networks can be found in many references such as, (Luger 2012 and Skapura 2002).

The performance of trained Back-Propagation neural networks is mainly evaluated using the Coefficient of Multiple Determination (R^2), the Correlation Coefficients (r), the Mean Absolute Error and the percentages of calculated results that were predicted within several accuracy intervals that range from 10% to 30% (NeuroShell-2 2008).

To train a Back-Propagation neural network that predicts the fracture intensity of oil aquifers, a set of 97 data points were used. Each one consisted of eight input attributes and one output parameter. While the input attributes were borehole depth (BD), gamma ray contribution from thorium and potassium (GR), thermal neutron porosity in selected lithology (NPHI), standard resolution formation density (RHOZ), hole caliper (HCAL), standard resolution formation photoelectric factor (PEFZ), apparent resistivity from computed focusing mode 1 (RLA1) and apparent resistivity from computed focusing mode 5 (RLA5), the outcome parameter was the fracture density. The near optimum network design was found to be eight input neurons, 15 hidden neurons and one output neurons. The learning rate and momentum were found to be 0.6 and 0.9, respectively. The results of this network are listed in Table 1.

Table 1. Developed Neural Network Performance Criteria

Parameters	Value
R^2	0.98
Mean Absolute Error	0.34
Correlation Coefficient (r)	0.99
Percentage within 10%	37
Percentage within 10%-20%	25
Percentage within 20%-30%	8
Percent over 30%	30

As presented in Table 1, while the high magnitude of the Correlation Coefficient (i.e. 0.99) suggests that the eight input attributes explain the variations in fracture densities to a very high extend, the high value of the Coefficient of Multiple Determination (i.e. 0.98) demonstrates the high potential prediction capability of the trained NN. The contributions of input variables to the prediction of the fracture densities are shown in Figure 3. As shown in Figure 3, the highest contributions are associated with borehole depth and Standard Resolution Formation Density.

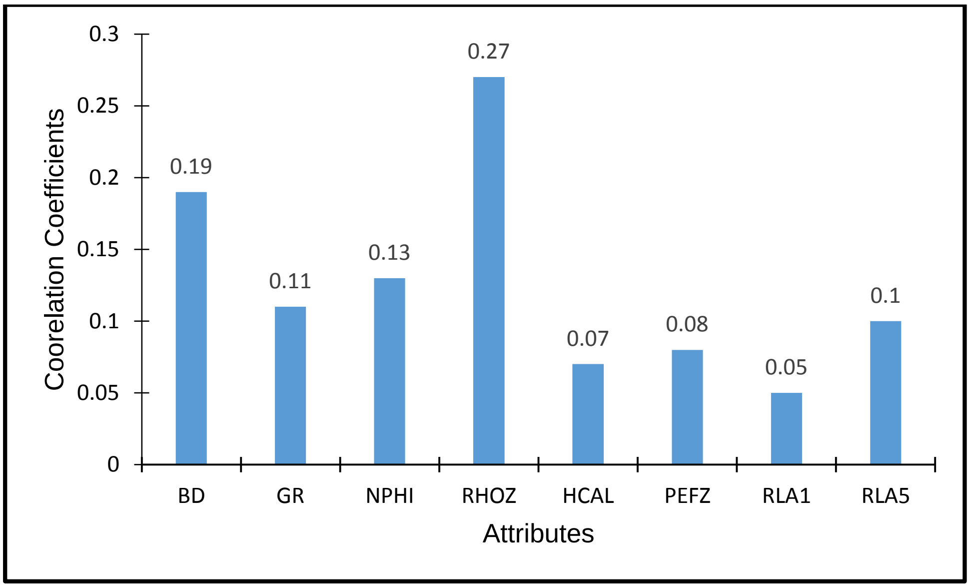

Figure 3: Correlation Factors.

CONCLUSION

A neural network based system that estimates the fracture density in oil reservoirs was developed. The system uses eight input attributes to perform its task. These attributes are borehole depth (BD), gamma ray contribution from thorium and potassium (GR), thermal neutron porosity in selected lithology (NPHI), standard resolution formation density (RHOZ), hole caliper (HCAL), standard resolution formation photoelectric factor (PEFZ), apparent resistivity from computed focusing mode 1 (RLA1) and apparent resistivity from computed focusing mode 5 (RLA5). The BD, RHOZ and NPHI were found to contribute to about 60% of the model prediction accuracy. The Correlation Coefficient (r) and the Coefficient of Multiple Determination (R^2) of the developed model are 99% and 98%, respectively. While the high magnitude of the Correlation Coefficient suggests that the eight input attributes explain the variations in fracture densities to a very high extend, the very high value of the Coefficient of Multiple Determination demonstrates the high potential prediction capability of the developed neural network model. Despite the fact that the developed model demonstrated high prediction capability on the used training set of data, rigorous testing strategy should be implemented. It is suggested also to use sensitivity analysis techniques to improve the performance of the proposed NN model.

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