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Adaptive Artificial Neural Network Approach for Permeability Prediction

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Abstract

Many oil reservoirs have heterogeneity in rock properties. Understanding the form and spatial distribution of these heterogeneities is fundamental to the success of reservoir description. Permeability is one of the fundamental rock properties to characterize flow potentials of the reservoir when subjected to applied pressure gradients. A number of mathematical models have been suggested in the literature to simulate and quantify this property. However, common to them are difficulties in being able to model appropriately various geological variations associated with any reservoir. This study explores the benefits of using the artificial neural network (ANN) and Nuclear Magnetic Resonance (NMR) log in the permeability predictive model development. ANN was used to capture the non-linearity issues between the dependent and independent variables while the transversal relaxation times (T2) data is capable of capturing intrinsic rock properties at pore scale level. Out of verified datasets available, 60% of the datasets were used for the training process and the remainder for testing and validation. The input data was transverse relaxation time data, its mean value of the bins, mean square value of the bins and the maximum value of the bins. The developed ANN was trained, tested and validated using MATLAB Neural network toolbox trained with backward propagation scheme. The result shows a very good performance of ANN when compared with other existing empirical correlations adopted in this study.

Keywords: Permeability; Heterogeneity; Artificial Neural Network; Reservoir; MATLAB.

1. Introduction

Permeability and porosity are among the most important rock properties. Of this two, permeability has been found to be a function of porosity as it measures the ease with which fluids flow through the rocks' pores under the influence of applied pressure gradient. Despite being a critical factor that affects the fluid flow within the rock, there has been no universally acceptable method for its estimation. Having a correct knowledge of permeability variation downhole is very important in reservoir characterization i.e. static modeling and dynamic reservoir modeling.

Many a time, several researchers have made considerable attempts at studying the factors that control permeability and most of them concluded that porosity, grain size, degree of sorting, cementation are among the key parameters accounting for permeability variation. Most of the permeability models are based on the assumption that there is a strong correlation between porosity and permeability [1-3]. Previous works on the prediction of permeability such as Timur-Coates, SDR model, Carman-Kozeny model and FZI concept have suffered from either overestimation or underestimation of the reservoir rock permeability and inability to produce appropriate permeability for specific lithology [3-4].

Furthermore, other researchers have also found that there exists an empirical relationship between capillary pressure, porosity, and permeability. Most of these models have been found to perform to an appreciable degree of confidence in sandstone reservoirs but fail in carbonate reservoirs because of diagenetic effect, grain size variation etc. [3-5]. Because of these setbacks, a better predictor that can handle these inherent unconformities will be good for modeling the reservoir complexities as the accuracy of any model depend upon the objective of the research and level of understanding of reservoir complexities.

Due to the inability of most empirical correlation to correctly model the reservoir rock complexities, an alternative was sought in Artificial Neural Network (ANN). According to Hamada and Elshafei, this model has been found to perform excellently in modeling this complex relationship [5]. Unlike regression analysis used in developing the most empirical correlations, ANN doesn't require the generation of any relationship between the input and output data as it has the ability to deduce the underlying relationship from the given training data. However, using ANN for identification purposes is more useful when a large number of data are available.

This research work unlike no other study the development of a generic artificial neural network model to predict permeability of reservoir rock within the uncored intervals. The outcome of this study will also be compared with existing correlations to compare its relative performance. MATLAB ANN and NMR were used without the addition of conventional log data that have been proved to contain uncertainties.

2. Methodology

2.1. Data collection and analysis

In this study, NMR logs and core data from an XYZ field were collected and analyzed. Furthermore, information gotten from the conventional logs were used to estimate permeability using existing correlations such as the Schlumberger-Dolls-Research and Timur- Coates permeability.

Prior to training the AANN model, the data sets must be analyzed to remove inconsistencies. Here, extreme values of permeability values were included in this study in order to the account for heterogeneity associated with the XYZ reservoir. In this study, the normalization algorithm used for transforming the data is the logarithmic type which has the ability to capture the effect of extreme values such as a low-permeable shale interval within a highly permeable formation. Also, this transformation will help reduces variability and makes the domain of its stochasticity uniform.

Using all the datasets, the first step was to identify different regions such as regions of low permeability, medium permeability, and high permeability. Fig 1 depicts the histogram that shows the skewed distribution of the permeability within the XYZ reservoir.

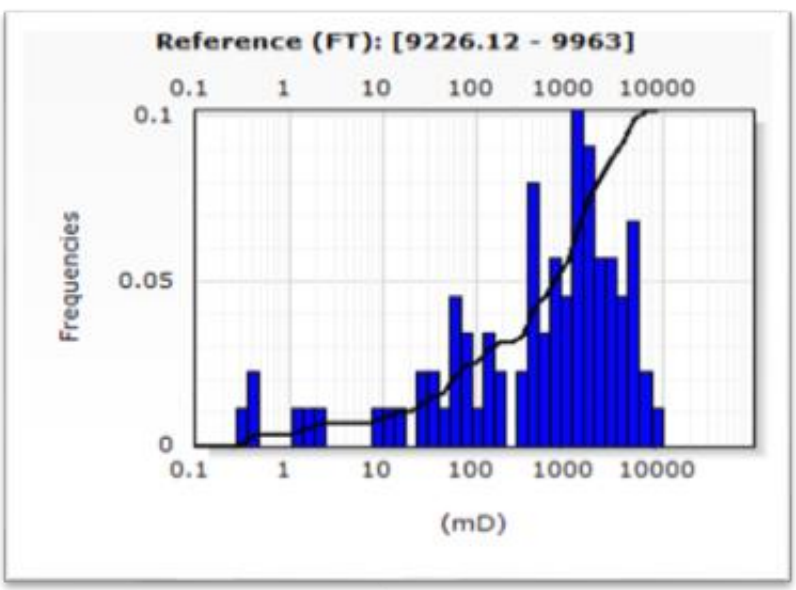


Figure 1. Histogram of the permeability distribution

2.2.Neural Network model development

Inputs, in this case, T_2 distributions, representing the variables that affect the output (permeability) of the network are fed to each of the neurons in the following layers with activation depending on their weighted sum of the inputs. Fig. 2a and 2b show the diagrammatic representation of a typical biological neural network and artificial neural network architecture respectively, depicting various component and characteristics used in model development.

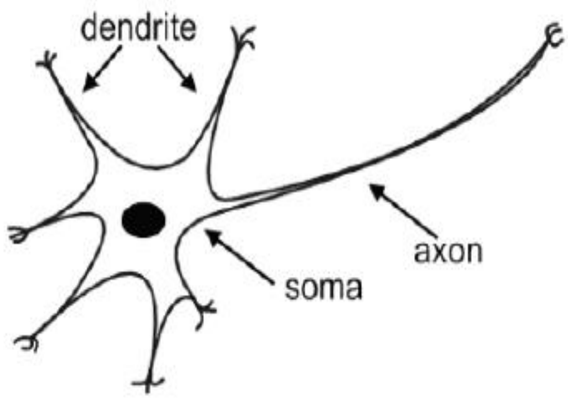


Figure 2b. Typical Artificial neural network

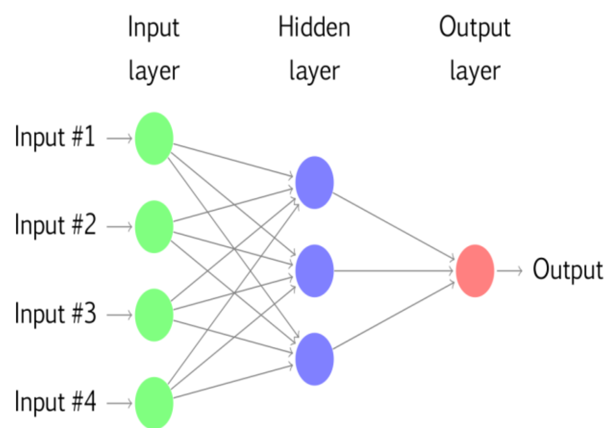
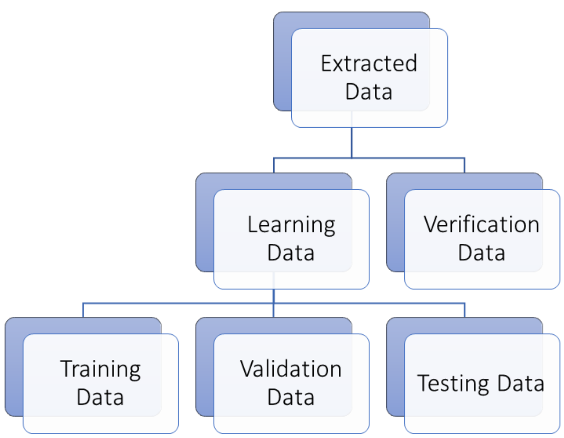


Figure 2b. Typical Artificial neural network



The network was trained to adapt the weights such that the error between the desired output and the network output is minimized. The summary of steps that were used in the development of the neural network model is as shown in fig. 3 The weight used was selected at random by the ANN toolbox itself. Two steps used in training the model include the feedforward computation and weight adaptation. The method of training used in this research is an adaptive training algorithm. Of the 69 available datasets, 60% of the available test data was used to train the network while the remaining data was used for model testing and validation.

The performance indices used to assess the accuracy of the developed model are summarized in Table 1. The model developed was used to predict permeability and statistically, the predictions were compared with the field and core data.

For more confidence and applicability of the developed model, the network was inspected against datasets that were chosen differently from those used to develop the model. It covered all the ranges of the input variables. After this testing and validation phase, the structure of the model earlier predicted was retained because of its acceptable precision. After the network has been validated, the permeability of given interval predicted using network was compared with that obtained from the core and empirical correlations including Schlumberger-Doll research model and Timur-Coates model. After the ANN has been trained and inspected by testing and validation, the final network developed was used to predict the permeability of the un-cored part of the reservoir given its NMR data.

2.3. Statistical analysis

In this phase, the Schlumberger Dolls research, Timur Coates and proposed Artificial Neural Network model were analyzed using performance indices summarized in Table 1.

Table 1. Summary of performance indices *(Arinkoola and Ogbe [6])*

Name of measure	Formula
Absolute deviation(AD)	$AD = \frac{1}{N}\sum_{i=1}^{N}(Pred.-Exp.)$
Average absolute deviation(AAD)	$AAD = \frac{1}{N}\sum_{i=1}^{N}/(Pred.-Exp.)/$
Root mean square error(RMSE)	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Actual - Predicted)^2}$
Average absolute percentage relative error	$AAPPRE = \frac{1}{N}\left[\sum_{i=1}^{N}/E_i/\right]$
Maximum error(Emax)	$E_{max} = Max/E_i/$ $E_{min} = Min/E_i/$ $E_i = \frac{Pred.-Exp.}{Exp.} \times 100$
Standard deviation(SD)	$SD = \sqrt{\frac{1}{N-1} \times \sum_{i=1}^{N} {E_i}^2}$

3. Results and analysis

As earlier stated that previous works on the estimation of permeability such as Timur-Coates, SDR, and Kozeny-Carman models have suffered from either overestimation or underestimation of the reservoir rock permeability because of their inability to produce appropriate permeability model for specific lithology. To confirm this assertion, a preliminary assessment of these models was performed with the result as shown in fig. 4, 5a and 5b.

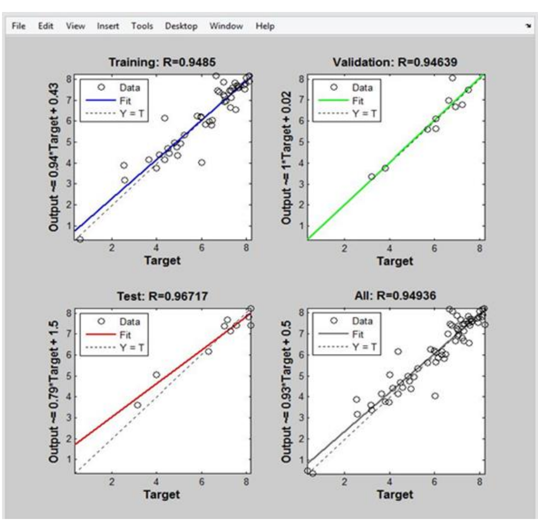


Figure 4. Performance evaluation of ANN training

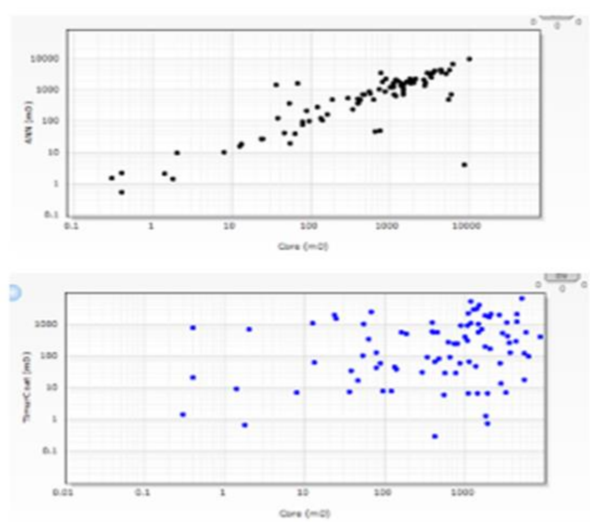


Figure 5a. Preliminary assessment of existing correlations

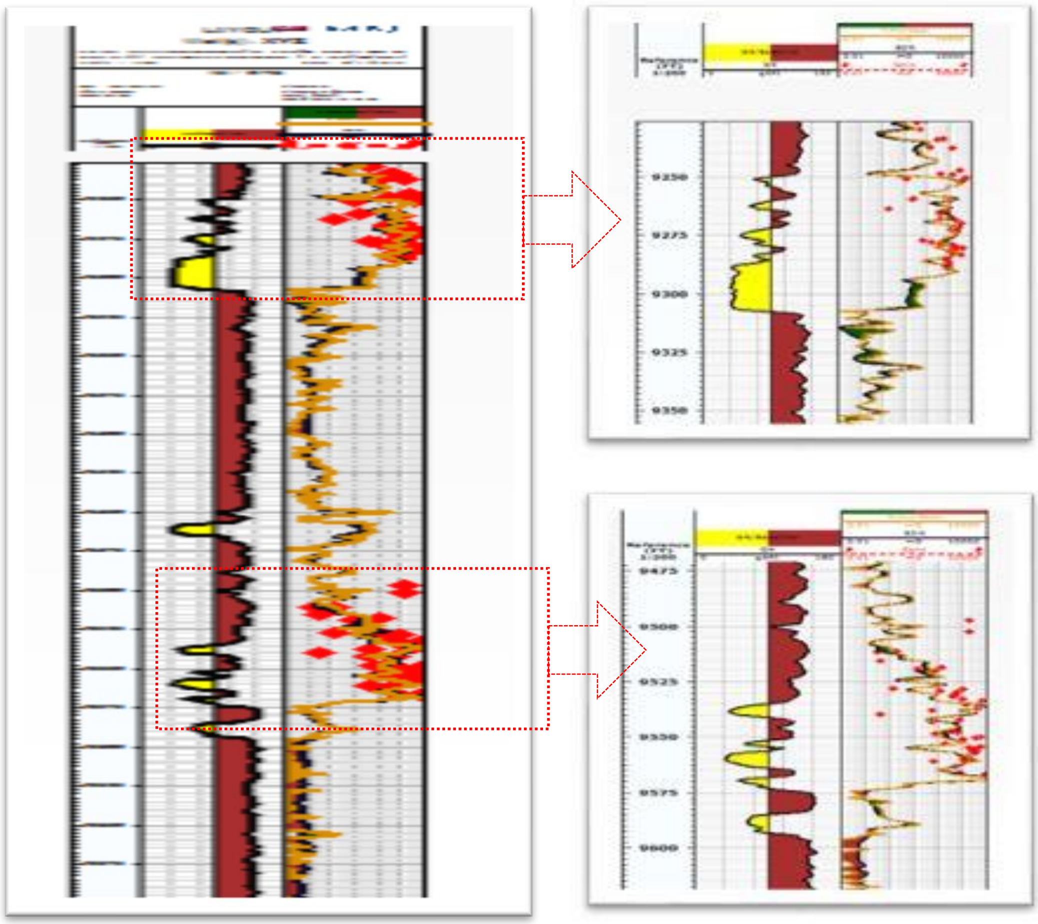


Figure 5b. Preliminary assessment of existing correlations

After the learning process, the following set of results were obtained. The regression plot (fig. 5) displays the network outputs with respect to estimate of the targets during training, validation, and test phase. For a perfect fit, the data should fall along a 45° line, where the network outputs are equal to the targets. From the assessment of this plot, it can be inferred that the neural model manages to properly interpolate the test data and achieves almost uniform performance on the entire log data. The correlation coefficients obtained for training, testing and validation are 0.9485, 0.9672 and 0.9464 respectively. For this problem, these coefficients are reasonably good and the developed model is capable of giving a realistic forecast of permeability where data are not available.

Figure 6a and 6b show the estimate of permeability using the developed model, studied correlations and core data. From the figure, it can be seen that the ANN model was able to model the complex nonlinear relationship between the petrophysical properties and it was also able to generalize the relationship between the properties in different facies. The use of arti-ficial neural network has overcome the problem of non- linearity that has led to underestimation and overestimation associated with the use of other existing empirical correlations. This will surely help petrophysical scientist and oil companies in estimating permeability in un-cored well once the T_2 distribution for each bin are available

The statistical evaluation of the existing correlations coupled with the proposed model is as shown in Table 2. Here, the estimates of permeability of the developed model were compared with each target output. From Table 2, statistical analysis shows the negligible difference between the estimate of using ANN but large differences using SDR and Timur-Coates when compared with the base value (core permeability). Although the model developed prediction is within an acceptable range, it can still do better if additional data are available.

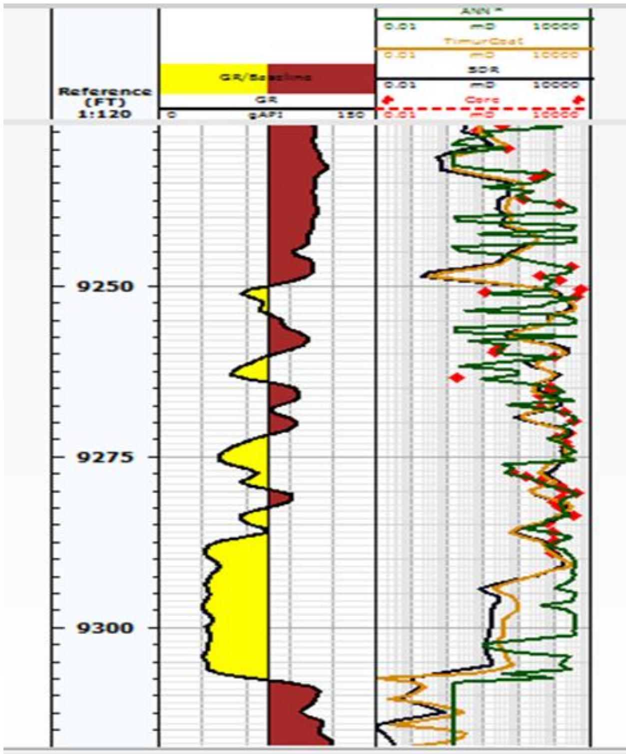


Fig. 6a. Well section 1 using the proposed ANN model

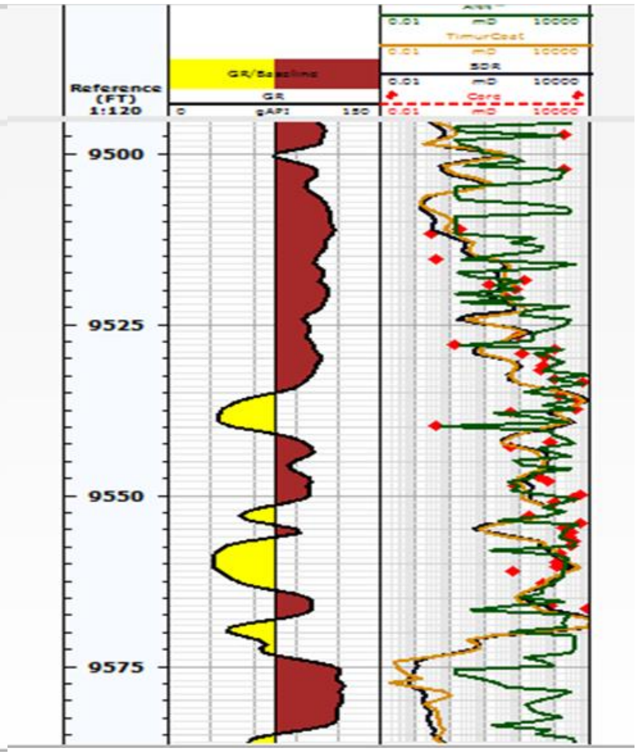


Fig. 6b. Well section 2 using the proposed ANN model

Table 2. Summary of performance indices

Measure	ANN	Timur	SDR
AD	0.02	2.29	2.43
AAD	0.62	2.29	2.43
RMSE	1.51	9.14	10.23
SD	0.61	0.31	0.28
Emax	6.09	16.68	28.48
AAPRE	0.66	0.17	0.32

The model developed using the artificial neural network presents a new and unique way in estimating reservoir permeability. The rock permeability estimated through this process is expected to less error prone because it mimics the way human being learn new things. It is also expected that the heterogeneities usually present in most reservoir were modelled accurately using the ANN.

4. Conclusion

From the results obtained it can be concluded that the prediction of permeability using artificial neural network had provided an accurate model for predicting permeability in oil and gas wells. It was also deduced that NMR derived permeability has shown good matching with core tests results. Also, that NN-predicted permeability from NMR decay times T_2 achieve very close values to the core permeability compared with other models. It is recommended to use the developed NN model to predict permeability from NMR data in other wells so as safe companies from incurring costs that could have been averted if they had used the model. It is also recommended to try different NN structures for possibly achieving improved results than those obtained by Feed Forward Neural Network and also a considerable amount of NMR data should be provided for future research because the NMR data gives a better representation of the hydrocarbon fluid present in the oil and gas bearing rock.

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