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New Approach for the Prediction of Klinkenberg Permeability In Situ for Low Permeability Sandstone in Tight Gas Reservoir

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Abstract

Tight gas reservoirs show challenges to geologists to characterize because of their tendency to be generally heterogeneous due to depositional and diagenetic processes. The value petrophysical properties are very valuable in static and dynamic reservoir modeling. This paper presents a prediction of Klinkenberg permeability by using artificial neural network, composite logs and core data in basin in western USA. The klinkenberg model approximates a linear relation between the measured gas permeability and the reciprocal absolute mean core pressure. This model has been a consistent basis for the development of methods computing the absolute liquid permeability of a core sample based on a single data point.

In tight gas reservoir with increasing in gas slippag (klinkenberg effect) cause to decrease in pore-throat size and permeability parameters. In advanced there were some method to determine Klinkenberg permeability in situ which can be obtained by measuring just routine air permeability and Klinkenberg parameter such as byrnes in 1997 & 2003 but these ways intensively depend on core permeability, so it needs some core plugs and inevitably we have to spend much time and money.

The goal in this study was to research about relationship between core Klinkenberg permeability and composite logs (gamma ray, density, neutron and formation resistivity and so on) by using MLP & Back Propagation methods (Artificial neural network) to characterize the Klinkenberg permeability in situ in 3 different wells in 3 stages (training, validation and application) with suitable core calibration. For two wells there is very good core calibration and the R2 is more than 0.7 in training and application processes.

The importance of evaluation of tight gas reservoir with high heterogeneity by using artificial neural network and conventional logs is spending less capital or time and finally obtaining reliable Klinkenberg permeability in situ.

Introduction

Tight gas reservoirs are defined as formations with permeability less than 0.1 millidarcy. Gas reserves in tight reservoirs constitute a significant percentage of the natural gas resources worldwide and offer tremendous potential for future reserve growth and production. Tight gas reservoirs often exhibit unusual characteristics that require more research on it. Reliable reservoir description and assessment of such low permeability tight gas reservoirs demand reliable laboratory permeability data.

Gas slippage is a non-Darcy effect associated with nonlaminar gas flow in porous media. These effects occur when the size of the average rock pore throat radius approaches the size of the mean free path of the gas molecules, thus causing the velocity of individual gas molecules to accelerate or "slip" when contacting rock surfaces.This phenomenon is especially significant in tight gas sands that are typically characterized by very small pore throats. During this process, the velocity of gas layer in the immediate vicinity of the solid walls of the capillary or porous medium is not zero, causing an increase in gas flow rate in porous sample. Klinkenberg who was one of the first to study and document gas slippage effects in porous media, showed the observed permeability to gas is a function of the mean core pressure. Furthermore, he observed that the gas permeability approaches a limiting value at an infinite mean pressure. This limiting permeability value, which is sometimes referred to as the equivalent liquid permeability1 or the Klinkenberg corrected permeability, is computed from the straight-line intercept on a plot of measured permeability against reciprocal mean pressure. In equation form, the line is defined by

$$k = k_\infty (1+ b\, p) \tag{1}$$

Equation (1) is also referred as Klinkenberg correlation, where P is the mean pressure, k is the apparent gas permeability observed at mean pressure, and k_∞ is the "true" permeability or Klinkenberg permeability at an infinite mean pressure. b is the gas slip factor, a coefficient depending on the mean free path of a particular gas and the average pore radius of the porous medium, as is given by

$$b=4c\, \lambda\, p/r \tag{2}$$

where λ is the mean free path of gas molecules, is the velocity gradient in the direction perpendicular to the wall, and c is a proportionality factor. where, r is the radius of a capillary or a pore. The idealized porous medium is that in which all the capillaries in the material are of the same diameter and are oriented at random through the solid material. Equation (2) suggests that the gas slip effect is significant in tight porous samples because of the extremely small pore size.

One of the methods for Klinkenberg effect prediction is using artificial neural network (ANN). The use of ANN eliminates some of the problems associated with costs and generalization of the developed models for the prediction of permeability distribution. ANN is a data processing system capable of learning and understanding complex relationships between inputs and output by the use of highly interconnected artificial neurons. ANN is capable of learning in order to recognize, classify and generalize. The learning process can be supervised, in which case, the input and output patterns are required or be un-supervised, which requires only the input patterns. Figure 1 shows the schematic diagram of an Artificial Neural Network. Back propagation form of Neural Network has been chosen among the available networks due to its ability to be designed, trained, and to generalize (predict) well on a wide variety of problem (Oyerokun, 2002). A Back propagation (BP) Network is a multi-layer Network with more than one hidden layers. It propagates the inputs activity forward while error is propagated backward to adjust the connection weights in order to improve its predictive capabilities. This is continued until a desired minimum error is achieved.

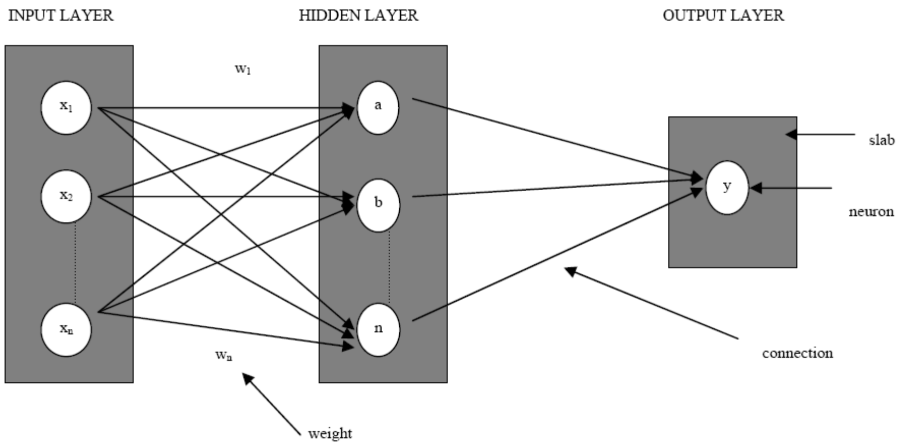

Fig.1: Schematic Diagram of a Neural Network with One Hidden Layer

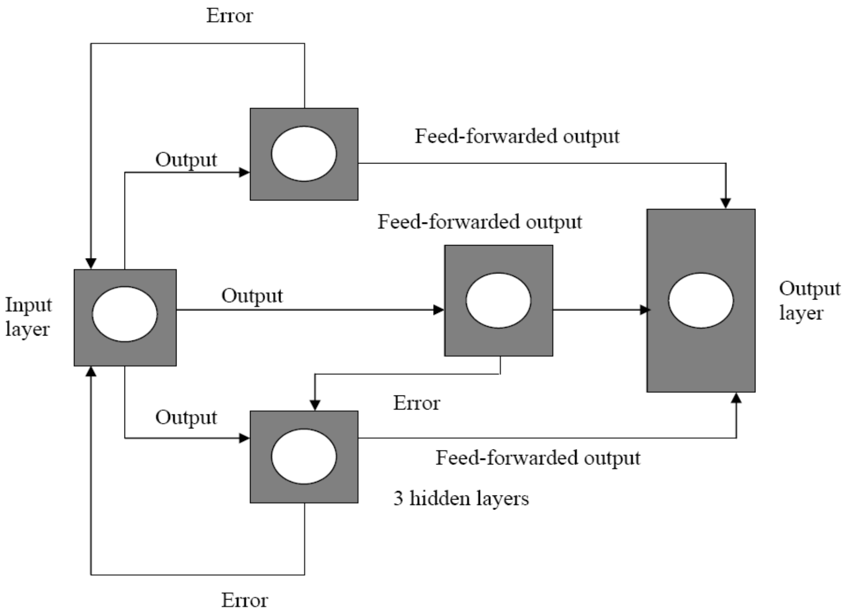

Fig.2: Structure of Back propagation Network (BPN) with 3 hidden layers

Back propagation learning algorithm

ANN is a mathematical system which can model the ability of biological neural networks by interconnecting many simple neurons. The neuron accepts inputs from a single or multiple sources and produces outputs by a simple calculating process with a predetermined non-linear function. A typical three layer network with an input layer (I), a hidden layer (H) and an output layer (O) is shown in Figure 3. The number of hidden layers can revolve from 1 or more layers.

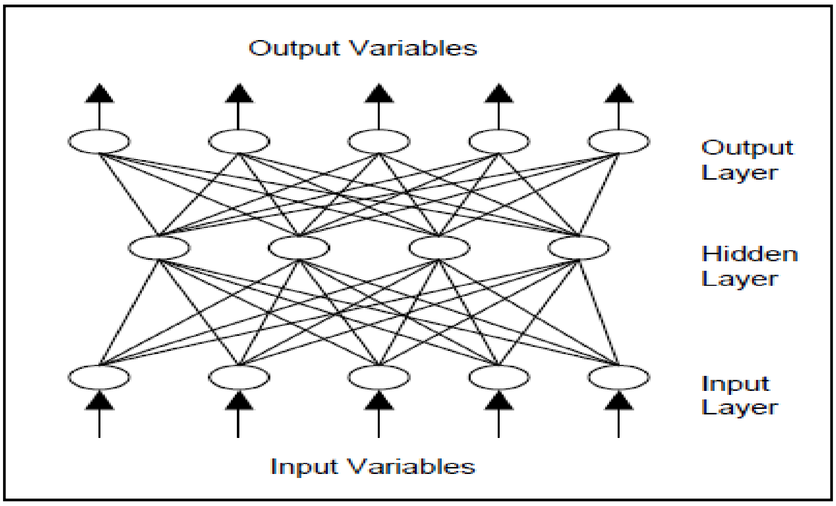

Fig.3: a view of MLP network

Each layer consists of several neurons and the layers are interconnected by sets of correlation weight. The neurons receive inputs from the initial inputs or the interconnections and produce outputs by transformation using an adequate non-linear transfer function. Different transfer functions are used in multi-layer feed forward neural network structures which tangent hyperbolic, logistic sigmoid and linear transfer functions are the most important transfer where are given by equations 3-6,respectively:

$$a = f(n) = \frac{1-e^{-2n}}{1+e^{-2n}} \tag{3}$$

$$a = f(n) = \frac{1}{1+\exp(-kn)} \tag{4}$$

$$a = f(n) = n \tag{5}$$

Which n is:

$$n = W * p + b \tag{6}$$

In above equations, a, p, W, b and k are output of transfer function, input vector, weight vector, bias and a constant parameter, respectively. In this paper, each of them is examined at different layers and structure during the training process in order to find out the desired ANNs.

BP, developed by Rumelhart, Hinton and Williams, is the most prevalent of the supervised learning models of ANN. Standard back propagation is a gradient descent algorithm which network weights move opposite the direction of performance function. In the learning process of BP, the interconnection weights are adjusted using an error convergence technique to obtain a desired output for a given input.

$$E = \frac{1}{2}\sum_k (T_k - A_k)^2 \tag{7}$$

In which T_k and A_k represent the actual and predicted values of output neuron, respectively, and k is the output neuron. The gradient descent algorithm adapts the weights according to the gradient error, which is given by:

$$\Delta W_{ij} = -\eta \times \frac{\partial E}{\partial W_{ij}} \tag{8}$$

Where η is the learning rate and the general form of the $\frac{\partial E}{\partial W_{ij}}$ term is expressed by the following form:

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n . A_i^{n-1} \tag{9}$$

Substituting equation (10) into equation (9), we have the gradient error as:

$$\Delta W_{ij} = \eta . \delta_j^n . A_i^{n-1} \tag{10}$$

In which A_i^{n-1} is the output value of sub layer related to the connective weight W_{ij}. δ_j^n is error signal, which is computed based on whether or not neuron j is in the output layer. If neuron j is one of the output neurons, then:

$$\delta_j = (T_j - Y_j).Y_j.(1 - Y_j) \tag{11}$$

If neuron j is a neuron of hidden layer:

$$\delta_j = [\textstyle\sum_j \delta_j . \left(W_{hy}\right)_{hj}].(1 - H_h)$$

(12)

Where H_h is the value of hidden layer. Finally, the value of weight of the interconnectivity neuron can be expressed as follows:

$$W_{ij}^m = W_{ij}^{m-1} + \Delta W_{ij}^m = W_{ij}^{m-1} + \eta . \delta_j^n . A_i^{n-1} \tag{13}$$

To accelerate the convergence of the error in the learning procedure, Jacobs proposed the momentum term with momentum gain, α, in equation.

$$W_{ij}^m = W_{ij}^{m-1} + \alpha . \Delta W_{ij}^{m-1} + \eta . \delta_j^n . A_i^{n-1} \tag{14}$$

In which the value for α is between 0 and 1.

Where t and a are target output and predicted output, respectively, and n is number of used data for network training or testing. Since in each run, both the network weights and training and testing data are selected randomly, noting this point is necessary that the resulted answers in each run are different from the other runs. Because of this, each of the used networks was operated 10 times and their results mean was considered as the network result. Also to prevent the occurrence of over fitting in network training stage, exerting training data to the network was stopped after 600 epochs.

Prediction by BP-ANN

The goal in this study was to research about relationship between core Klinkenberg permeability and composite logs (gamma ray, density, neutron and formation resistivity and so on) by using MLP & Back Propagation methods (Artificial neural network) to characterize the Klinkenberg permeability in situ in 3 different wells in 3 stages (training, validation and application) with suitable core calibration (figure 4&11)

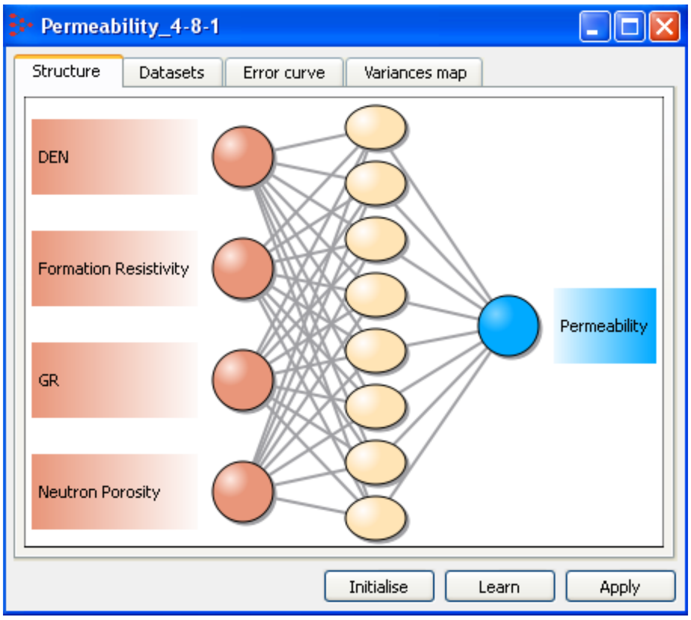

Fig.4: Structure of BP-ANN, 4 neurons in input layer, 10 neurons in hidden layer and 1 neuron in output layer.

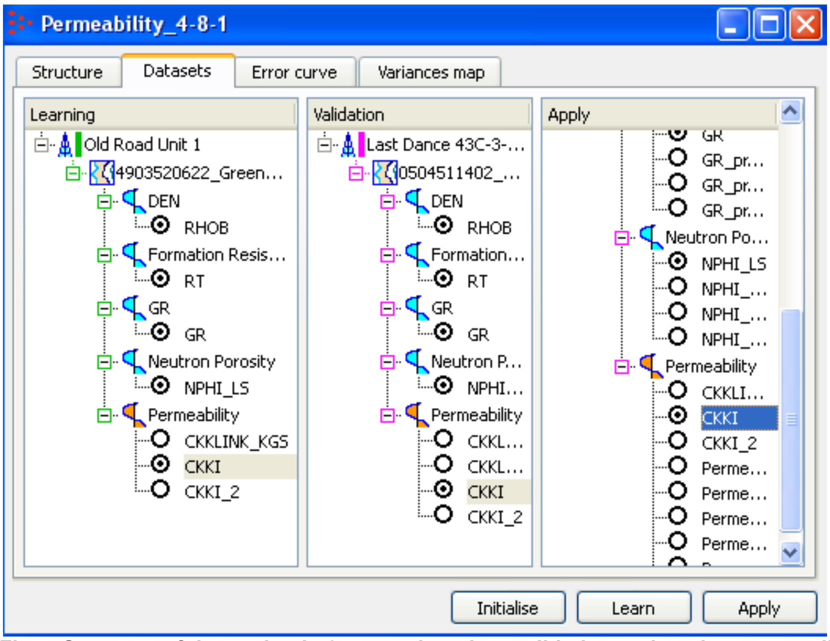

Fig.5: Structure of data using in 3 stages learning, validation and apply or generalization.

For two wells there is very good core calibration and the R^2 is more than 0.7 in learning and application processes

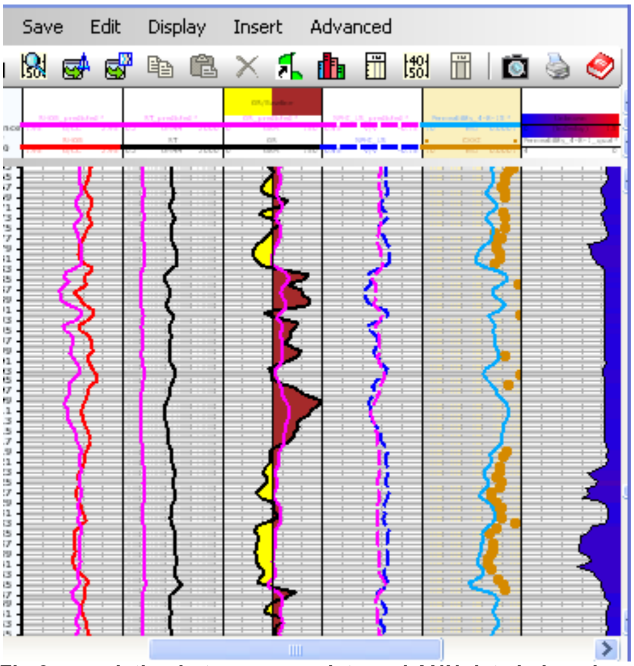

Fig.6: correlation between core data and ANN data in learning stage in no. well 1

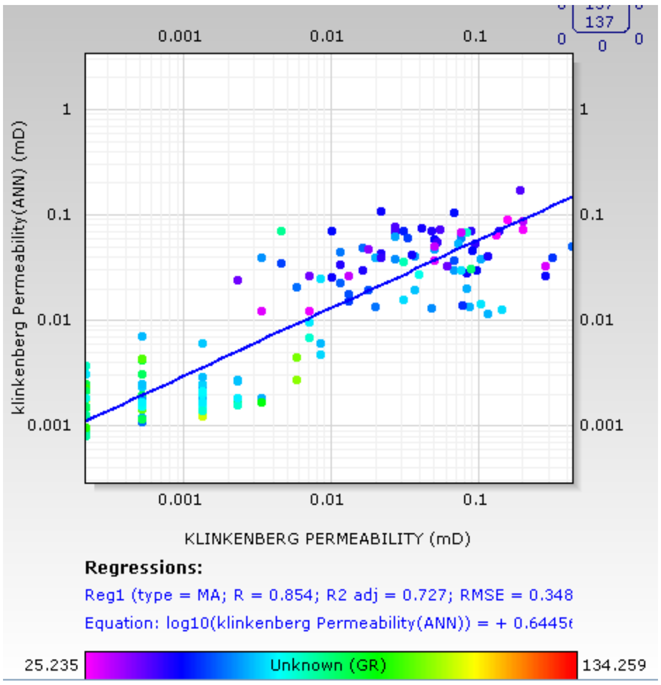

Fig.7: The correlation coefficient between BP-ANN simulated and core Klinkenberg permeability

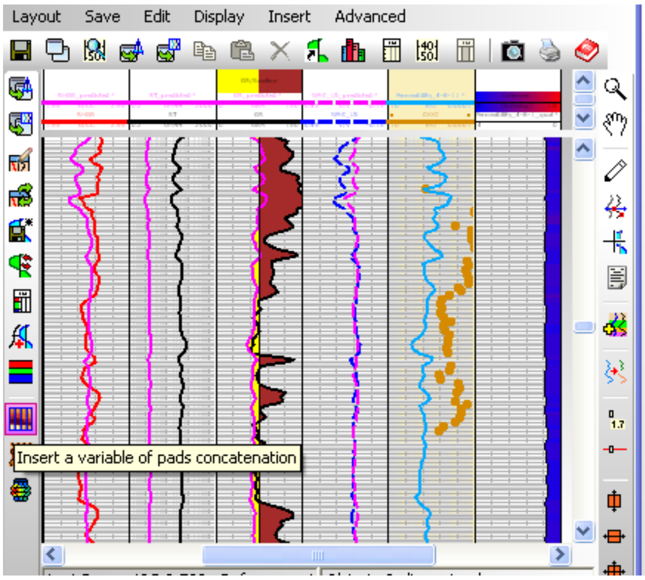

Fig.8: correlation between core data and ANN data in validation stage in no. well 2

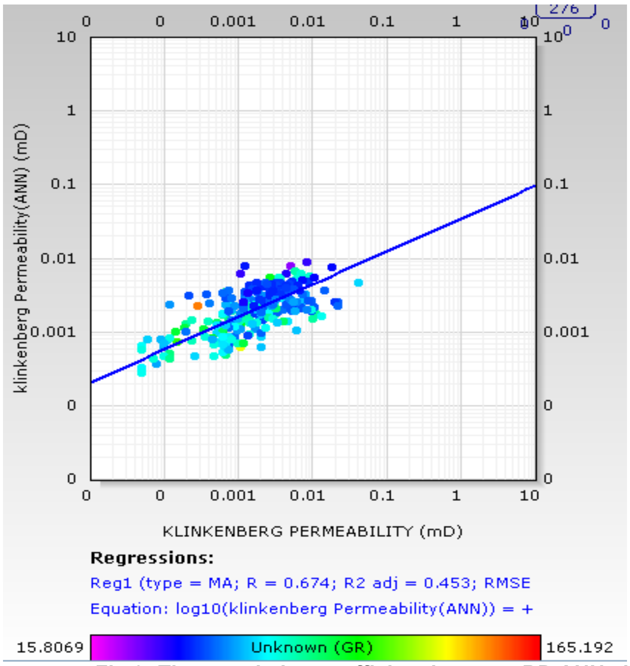

Fig.9: The correlation coefficient between BP-ANN simulated and core Klinkenberg permeability in no. well 2

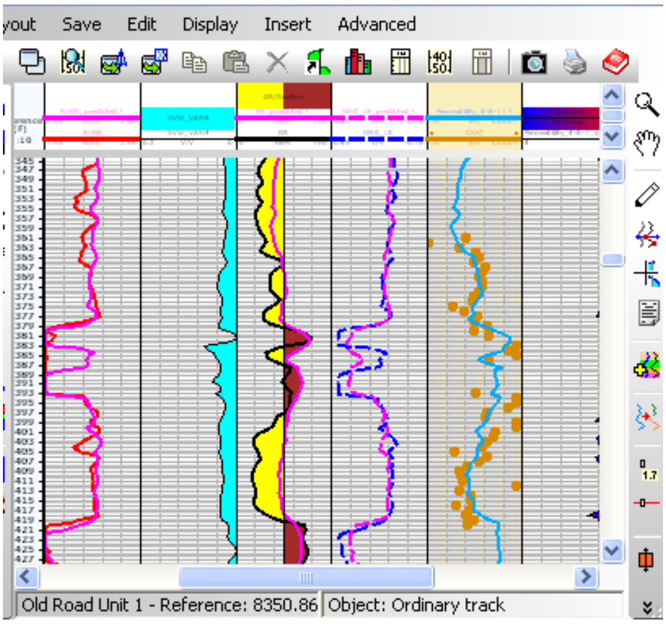

Fig.10: correlation between core data and ANN data in apply stage in no. well 3

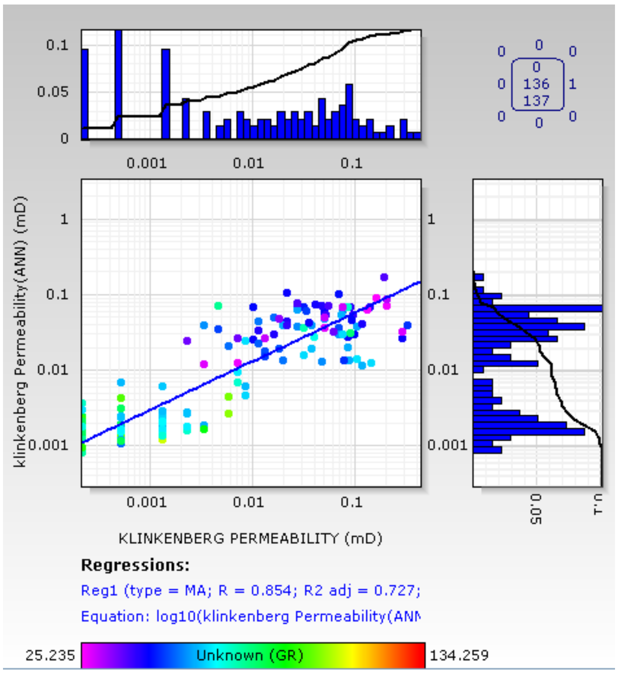

Fig.11: The correlation coefficient between BP-ANN simulated and core Klinkenberg permeability in no. well 3

Finally, Klinkenberg permeability is simulated by neural network in wells No. 4 (figure 12) and the following results are obtained:

- The correlation coefficients between BP-ANN simulated Klinkenberg permeability and techlog Software Klinkenberg permeability is satisfied.

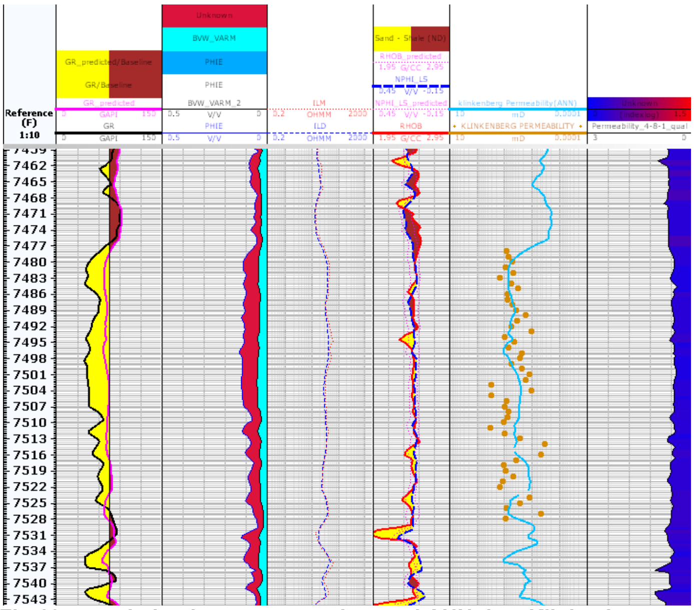

Fig.12: correlation between core data and ANN data Klinkenberg permeability in generalization stage in no. well 4

The importance of evaluation of tight gas reservoir with high heterogeneity by using artificial neural network and conventional logs is spending less capital or time and finally obtaining reliable Klinkenberg permeability in situ.

Conclusion

The goal in this paper was to demonstrate a methodology using ANN to predict the Klinkenberg permeability in situ where core is not available and composite logs such as gamma ray, density, neutron and formation resistivity by using MLP & Back Propagation methods. A reasonably good math is observed between ANN predicted Klinkenberg permeability and core Klinkenberg permeability.

As ANN is a multiple nonlinear or ill-defined system, this methodology is preferable to regression analysis. One can use these results in a reservoir simulation model to reduce the error in measurement of Klinkenberg permeability and get better characterization of reservoir. This enhanced accuracy will help in decision making for better reservoir development program.

Also good quality of the log data and core Klinkenberg permeability is necessary for accurate ANN prediction.

In this paper by using MLP & Back Propagation methods, characterize the Klinkenberg permeability in situ in 3 different wells in 3 stages (training, validation and application) with suitable core calibration For two wells. However there is suitable core match and the R^2 is more than 0.6 and 0.7 in learning and application processes.

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