4 4160 - 1

Shale Gas Rock Properties Prediction using Artificial Neural Network Technique and Multi Regression Analysis, an example from a North American Shale Gas Reservoir

M. Reza Rezaee
Department of Petroleum Engineering, Curtin University of Technology, Perth, WA
r.rezaee@exchange.curtin.edu.au

Roger M. Slatt
School of Geology and Geophysics, Oklahoma University, OK, USA,
rslatt@ou.edu

Richard F. Sigal
School of Petroleum and Geol. Engineering Oklahoma University, OK, USA,
rsigal@ou.edu

SUMMARY

Estimation of reservoir parameters has always been a challenge for shale gas reservoirs. This study has concentrated on neural network technique and multiple regression analysis to predict reservoir properties including porosity, permeability, fluid saturation and total organic carbon content from conventional wireline log data for a large North American shale gas reservoir. More than 262 core analysis data from 3 wells were used as "target" and "response" for neural network and multiple regression analysis. Common log data available in three wells including GR, SP, RHOB, NPHI, DT and deep resistivity were used as "input" and "predictor".

This study shows that reservoir parameters could be better estimated using the neural network technique than through multiple regression. The neural network method had a correlation coefficient greater than 80% for most of the parameters. Although providing a set of algorithms, multiple regression analysis was less successful for predicting reservoir parameters.

Key words: Shale Gas reservoir, Artificial Neural Network, Multi Regression Analysis, North American

INTRODUCTION

Routine and known algorithms for calculation of reservoir properties from wireline log data have been proved to be unsuccessful for shale reservoirs. Accurate calculation of porosity from log data requires detail knowledge of matrix and pore fluid properties such as density and transit time. In typical reservoirs these factors can be obtained accurately. But in shale reservoir there is a significant uncertainty in matrix and pore fluid properties. Presence of organic material associated with adsorbed fluids, clays with different physico-chemical properties and mixture of different minerals embedded in clays makes it difficult to obtain accurate factors for porosity estimation in shale reservoirs.

Permeability estimation from conventional log data is still a challenge for typical reservoirs. For shale reservoirs with very complex and microscopic pore network, permeability calculation can not be accurate using existing algorithms.

For fluid saturation estimation uncertainty exists for true formation resistivity (Rt) and formation water resistivity (Rw) values. Rt can not be accurately calculated since organic material can have unpredicted effect on Rt depending on level of thermal maturation, mode of occurrences in the matrix and their degree of compaction.

The above mentioned shortcoming of using conventional methods urged us to apply neural network method and multi regression analysis for predicting reservoir properties from log data.

METHOD AND RESULTS

Artificial Neural Network

Application of intelligent system such as artificial neural networks, fuzzy logic, etc., in oil industry has proved to be a valuable tool for rock property prediction (e.g., Rezaee et al., 2006 and 2007; Kadkhodaie et al., 2006). A neural network is a mathematical algorithm that can be trained to solve a problem. Artificial neural networks are adaptive and parallel information-processing systems that have the ability to develop functional relationships between data and to provide a powerful toolbox for nonlinear, multidimensional interpolations. Artificial neural networks can recognize highly complex patterns within a data set. This feature of neural nets makes it possible to capture the existing nonlinear relationships that are normally not well understood between input and output parameters. The basic elements of a neural network comprise neurons and their connection strengths (weight). The structure of a network defines how the neurons in different layers are connected. Neural networks can be classified by the way they are trained, using either supervised or unsupervised learning. In supervised learning the neural network starts with a training dataset for which we know both the input and output values. The neural network algorithm then learns the relationship between the input and output from this training dataset, and finally applies the learned relationship to a larger dataset for which we do not know the output values. In unsupervised learning, the neural network is presented with a series of inputs and let the neural network look for patterns itself. In a typical neural data processing procedure, the database is divided into two separate portions called training and test sets. The training set is used to develop a desired network. In this process, the desired output in the training set that is used to help the network adjust the weights between its neurons (supervised training).

Artificial Neural Network Results

In this study, a back propagation network was used. A back propagation artificial neural network (BP-ANN) is a supervised training technique that sends the input values forward through the network and then computes the difference between the calculated output and the corresponding desired output from the training dataset. This error is then propagated

0812 3385

backward through the net and the weights are adjusted during a number of iterations. The training stops when the calculated output values best approximate the desired values. In this study, a three layered BP-ANN was used and a sigmoid function producing outputs in the range of [0, 1] was used as a transfer characteristic for each neuron in the hidden and output layers. 262 core analysis data including porosity, permeability, water saturation (Sw), gas saturation (Sg) and total organic carbon (TOC) were used for output layer. Output layer included one neuron for each output data. Six inputs including GR, SP, RHOB, NPHI, DT and deep resistivity logs were used in the first layer. Number of neurons in the hidden layer was 3. The three layered neural network was trained using the Levenberg-Marquardet training algorithm.

In this study 90% of the data was used for training set and 10% for testing set. To get the best results, different set of inputs was tried for each output. Table 1 shows the set of inputs for each output and their correlation coefficient.

Table 1 – Input sets used for ANN

Outputs	Inputs						R^2
	GR	SP	RHOB	NPHI	DT	AT90	
Porosity	√		√	√	√		0.84
Perm.	√	√	√	√	√	√	0.80
Sw		√	√	√		√	0.86
Sg		√	√	√		√	0.87
TOC	√	√	√		√	√	0.72

Figures 1 show the cross-plot of core data versus ANN results. Correlation coefficient for most of the cases is more than 80%.

Multiple Regression Analysis

Multiple regression is an extension of the regression analysis that incorporates additional independent variable in the predictive equation. The main reason of multiple regression is to find the relationship between several independent or predictor variables. Regression analysis has been used frequently as a main tool to find the relationship among reservoir properties including porosity and permeability.

In this study, log data including GR, SP, RHOB, NPHI, DT and Deep resistivity were used as "predictors" and core data including porosity, permeability, fluid saturation and total organic carbon content were used as "responses". Table 2 shows developed equations from regression analysis. Figures 2 show the crossplots of reservoir parameters obtained from core analysis versus those calculated from the equation showed in Table 2. In all of the cases the correlation coefficient is less than those from artificial neural networks.

Table 2 - Empirical equations developed from regression analysis using all data. R^2 values show correlation coefficient between measured and calculated parameter

Equations	R^2
Porosity = 32.3 - 0.00356 GR + 0.0137 SP - 12.4 RHOB - 10.1 NPHI + 0.105 DT-0.000534 AT90	60.6
K(nD) = 2323 + 0.142 GR - 0.802 SP - 805 RHOB - 1281 NPHI + 0.99 DT - 0.103 AT90	41.4
Sw = - 78.8 - 0.0607 GR + 0.130 SP + 37.7 RHOB + 157 NPHI + 0.027 DT - 0.0186 AT90	49.1
Sg = 169 + 0.0558 GR - 0.132 SP - 35.9 RHOB - 163 NPHI + 0.027 DT + 0.0147 AT90	50.1
TOC = 23.8 + 0.0140 GR - 0.00717 SP - 8.55 RHOB - 1.88 NPHI + 0.0033 DT- 0.00047 AT90	34.6

CONCLUSIONS

The results of this study show that reservoir parameters such as porosity, permeability and fluid saturation could be better estimated using the artificial neural network technique than through multiple regression. The neural network method had a correlation coefficient greater than 80% for most of the parameters. Although providing a set of algorithms, multiple regression analysis was less successful for predicting reservoir parameters.

REFERENCES

Rezaee, M.R., Kadkhodaie Ilkhchi, A., and Mohammad Alizadeh, P., 2007. Intelligent approaches for synthesizing of petrophysical logs. J. Geophys. Eng. (in press).

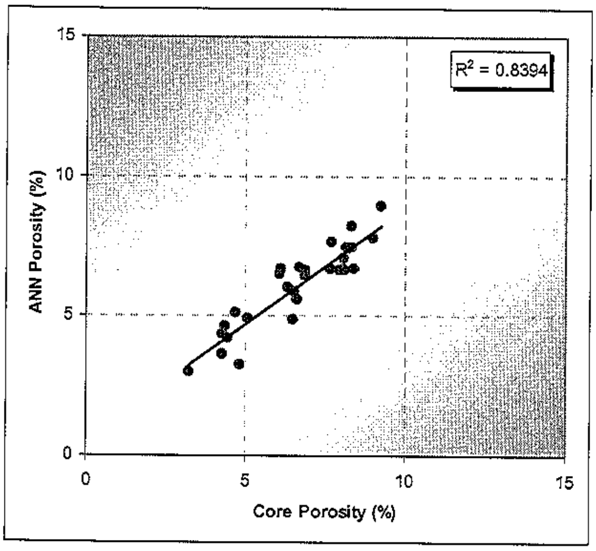
Rezaee, M.R., Kadkhodaie Ilkhchi, A., and Barabadi, A., 2007, Prediction of shear wave velocity from petrophysical data utilizing intelligent systems: An example from a sandstone reservoir of Carnarvon Basin. Journal of Petroleum Science and Engineering, 55, 201-212.

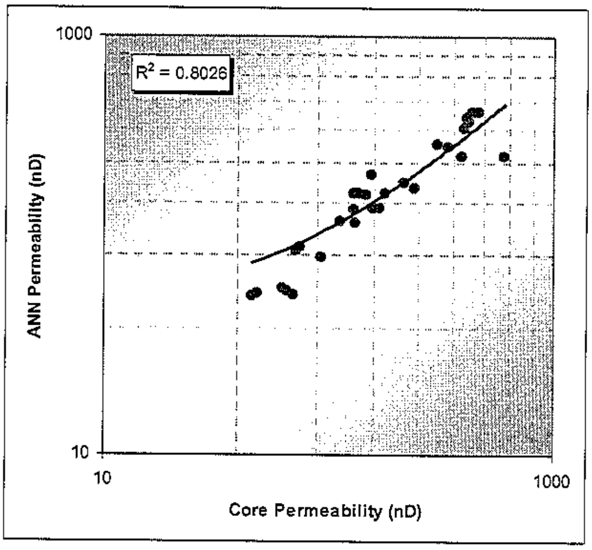
Rezaee, M.R., Jafari1, A., and Kazemzadeh, E., 2006, Relationships between permeability, porosity and pore throat size in carbonate rocks using regression analysis and neural networks. J. Geophys. Eng. 3, 370–376.

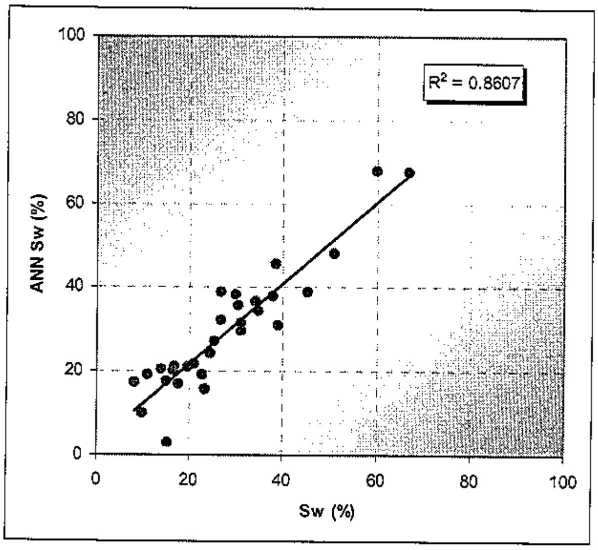
Kadkhodaie Ilkhchi1, A., Rezaee, M.R., and Moallemi, A., 2006, A fuzzy logic approach for estimation of permeability and rock type from conventional well log data: an example from the Kangan reservoir in the Iran Offshore Gas Field. J. Geophys. Eng. 3, 356–369.

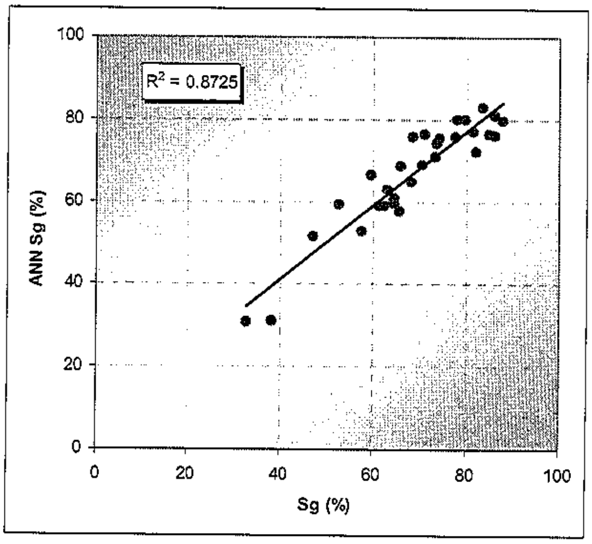
Rezaee, M.R., Nikjoo, M., Movahhed, B., and Sabeti, N., 2006, Prediction of effective porosity and water saturation from wireline logs using artificial neural network technique. Journal of Geological Society of Iran, 1, 21-27.

Rezaee, M.R., Slatt, R., and Kadkhodaie Ilkhchi, A., 2006, Application of Intelligent Systems for Generating Wireline Logs. Earth Science Journal, School of Geology and Geophysics, University of Oklahoma.









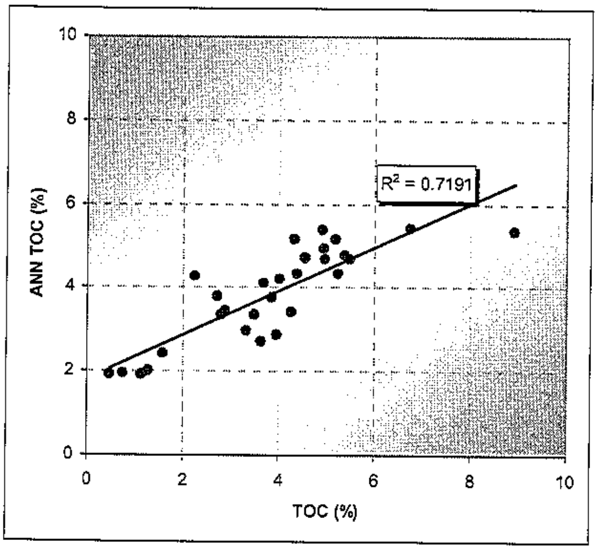


Figure 1 - Core analysis data versus artificial neural network results for test data.

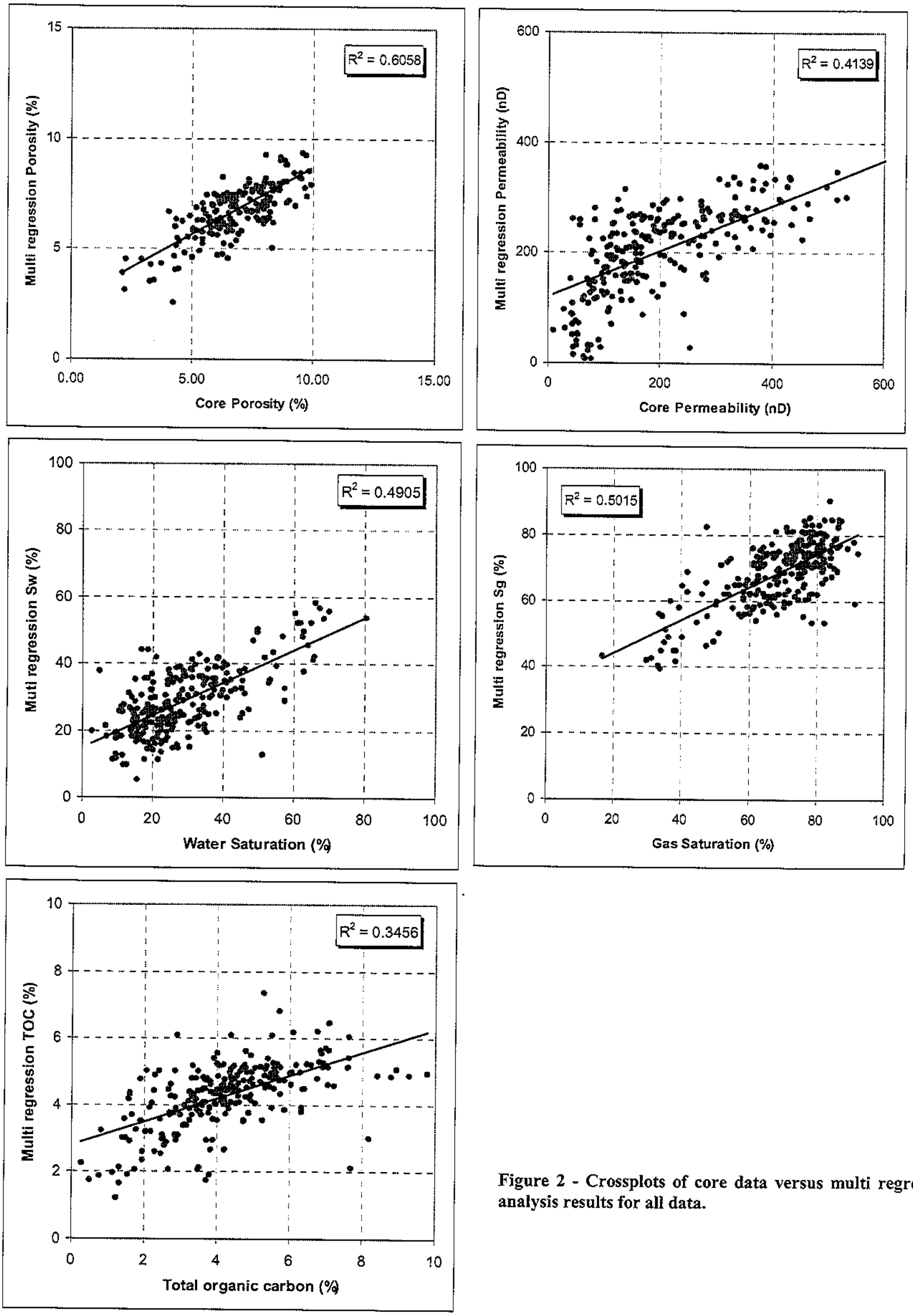


Figure 2 - Crossplots of core data versus multi regression analysis results for all data.