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Full Length Research Paper

Estimation of permeability using artificial neural networks and regression analysis in an Iran oil field

Abdideh, Mohammad

Department of Petroleum Engineering, Omidiyeh Branch, Islamic Azad University, Omidiyeh, Iran.
E-mail: abdideh@iauo.ac.ir.

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Porosity and permeability are two important parameters to be considered in evaluating the characteristics of an oil field. The permeability is the key parameter in describing a hydrocarbon reservoir. In fact, knowing the exact values of permeability is an effective, efficient and important tool for engineers in the oil production process and management of a field. Over the years, these two petrophysical parameters have been derived using core and well tested data; however, the results obtained using the two methods are accurate, but not sufficient to describe the full field, because these methods are not applicable in many cases. Recently, an artificial neural network technique was introduced, and has been found very useful in various areas of sciences and engineering especially in petroleum engineering. In this study, we have combined regression analysis techniques and neural networks methods to estimate permeability from well-logging data obtained in part of an Iran's oil fields. Comparing the results from this study with conventional techniques, indicate that these methods have fairly and reasonably predicted the permeability. But it was observed that the artificial neural network has better results than the other method.

Key words: Reservoir rock, permeability, petrophysical data, logging, neural networks, regression analysis.

INTRODUCTION

Characterizing reservoirs is an important task for petroleum engineers. A useful management strategy can be applied only when the spatial distribution of rock elements and very high detail is obtained. Permeability is defined as the ability of a reservoir to allow fluids to flow or transit in it. The content of oil or gas is not absolutely enough for a producer reservoir. The flow of these hydrocarbons is upward to the surface, which can be stored preciously in this reservoir. The flow of fluid is possible just when this reservoir have significant numbers of large, well-connected pores. Permeability been an important characteristics of reservoir rock is very difficult to predict and calculate but commonly calculated by analyzing core samples and well tested data. These are very expensive method and all wells in a field have not core, therefore obtaining the permeability values is one of the major problems in oil fields in which the core data are poor or low.

In Iran's oil fields, the permeability data obtained from different parts of the field are available. Petroleum engineers often use regression analysis as the main tool to obtain the relationship between these values. In this study, the assumption is that a linear or nonlinear function model showing the relationship between permeability and other rock properties is sufficient.

Analyses of key parameters such as reservoir permeability using data from petrophysical logging methods are useful and cost-effective in terms of cost, and time to assess the production potential of oil and gas reservoirs (Perez et al., 2005). In recent years, neural networks have emerged as powerful tools to model complex systems. The neural network analysis method enables the estimation of permeability using various algorithms with sparse analog data as input. Since in neural networks the data analysis are carried out in parallel and distributed method, their ability to recognize complex relationships between multiple variables can be presented to the neural network.

The purpose of this study is to establish an existing relationship between different parameters that is obtain from well log data, and to predict the relative permeability values from wells that do not have sufficient core data.

Artificial neural networks

Artificial neural networks are computational model that is inspired by biological neural networks. The network is functioning like a human brain function and one of the interesting features is that they have the ability to learn. It should be noted that learning in artificial neural networks is limited and what is considered is the computational ability of these networks. A network consists of units called nerve cells or neurons and has the ability to produce desired output data sets by using a bunch of input data. Each of these input and output data can be assumed as a vector. To train a network, input vectors are applied to consecutive and each cell will receive multiple signals to the network inputs (Jafri et al., 2012).

Neurons in a network, depending on their performance put on certain layers. Each network has at least three layers including input layer, middle layer is called the hidden layer and output layer (Gentry, 2003). Selecting the type and number of inputs has a big impact on the quality of network performance. Excessive and unnecessary use of the number of dependent parameters will result in the complexity of the network size and its poor performance. Also the access and use of data with low error rates is important.

Multiple linear regressions

Studies have shown that multivariate methods can be simultaneously applied in the analysis of several variables. Access and creation of more favorable results from these methods require large true sample data because these methods have high sensitivity to false information and entering such data may lead to gross errors in the results. Moreover, the use of these variables must be normally distributed and change to follow a linear relationship. In fact, multiple regressions are desired for relationship between a series of independent variables with a variable expression.

If we have independent variables x1, x2 ,..., xn, if linear relationship between them and the dependent variable y is to be created, the following relationship must be established between them:

$$y = a0 + a1x1 + a2x2 + \dots + anxn + e$$

In this regard, the values a1, a2... are the regression coefficients. These coefficients depend on the parameter estimates. If in one sides of the equation, the mathematical expectation is taken, thus, the mathematical expression of the error (e) will be zero, and one can re-write as:

$$E(y) = a0 + a1x1 + a2x2 + \dots + anxn$$

E (y) is in fact, the expected value, and the amounts under the influence of variables x1, x2... xn.

DATA AND PROCESSING

Geological studies are reviewed

The studied oil field is in southwest of Iran, it was studied and there is no surface exposure found there, the underground exploration seismic data shows the oil structure, and the first exploration well drilled in 1963 proved the abundance of hydrocarbon in Asmari and Bangestan reservoir.

The field has three different reservoirs namely: Asmari, Bangestan and Khami. The main producing mechanism is the water drive mechanism that is due to the existence of strong reservoir, so the average pressure drop trend of reservoir is about 0.56 psi/ MMbbl produced oil. The structure of the field follows the Zagros trend (NW-SE) and have significant quantities of oil in the reservoirs Asmari and Bangestan.4-2-Petrophysical studies.

Well logging

Many wells have been drilled for exploration and field development operations purposes. Also, nearly all of these well have been logged and their petrophysical parameters derived them. Data obtained from these logs that were very effective in the formation of petrophysical evaluation include the following: GR, Sonic, NPHI, RHOB, Resistivity, Sw, etc.

Core studies

Information obtained from this core data, including horizontal and vertical permeability, porosity and density, were studied and measured in the laboratory. The limitations in terms of administrative costs and time duration of which the core is taking to the core operations centre has a higher economic implication (Tiab and Donaldson, 2004) But, such data in the design and analysis models is inevitable because the information to be obtained from the core, are useful and valuable (Figure 1).

Determination of permeability using multiple linear regression analysis

One of the accurate estimation of petrophysical studies is permeability prediction in wells that are not possible for any reason. Petroleum engineers use regression analysis as the main tool to relate parameters such as porosity and permeability.

In this calculation the engineers usually assume that there is a linear or nonlinear relationship between permeability, porosity and depth. In other words, the relationship between rock permeability and other parameters is assumed adequately to be linear or nonlinear functions.

A common method for estimating permeability is to use porosity-permeability cross-plot obtained core data. An example of the linear regression equation and the non-linear regression equations is shown in Figure 2.

Determination of permeability using artificial neural network

The first and most important step in preparing data for modeling by

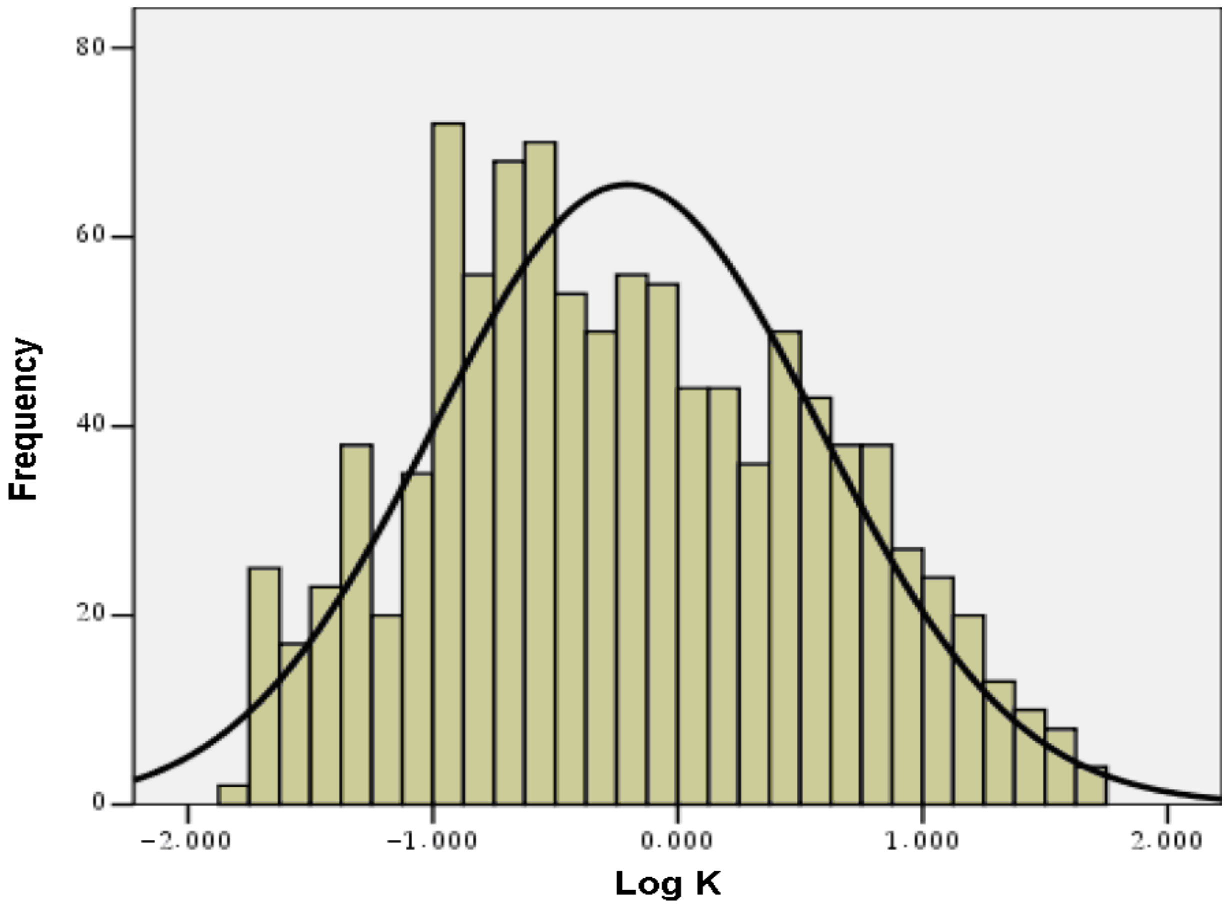


Figure 1. Core permeability data histograms

neural networks is to prepare data for train, test, and validation. The test set of data that tests the generalization ability of the model should be a representative of all data set (Yuqi et al., 2003). Inmany cases a small number of data for the test data remains, so the best data that is indicative of the repository for all data is very important and very difficult.

According to the available number of data we assigned 30% of data points to test and validation data sets (15% to test and 15% to validation data) and 70% data is training data. Each set of training data, testing and validation should be included in all wells and all the sections and subsections, also the three sets of data, including permeability data of all intervals (Mohaghegh et al., 1994).

Different models of neural networks are available and they are used for a specific purpose. To achieve our goal of using neural networks for reservoir characterization, we use Feed forward back propagation neural networks technique.

One of the major problems with this type of network is that the network should be so trained using the composition of the network, that is, the (mean square error) in order to, minimize the overall error. Another important issue is to find the optimal number of neurons and hidden layer and select the best appropriate function. Finally, a network with two hidden layers, with the best performance in the estimation of permeability data for training, testing and validation was found. So the final network which is selected has two hidden layer and one output layer.

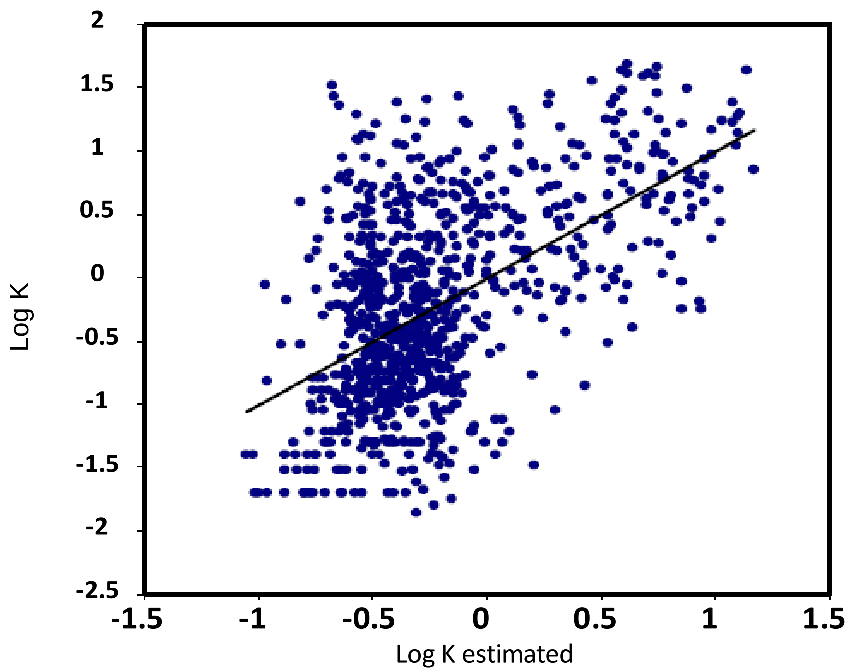
One main problem in building a model is finding the optimal number of neurons. The number of neurons has more effect on models than the number of layers. In determining the optimal number of neurons, the number of neurons in each layer and the total number of neurons affects the performance model. Two different layers network (2 hidden layers) were tested with the number of neurons. Here, only results of models with 1×15×20 grid, 1×10×13 and 1×6×9 were investigated. The first number is the number of neurons in the first hidden layer, the second number is the number of hidden neurons in the second hidden layer and third number is the number of neurons in output layer.

Because the network has one output (permeability), so the output layer has one neuron. The number of input parameters is eight including depth, conductivity, sonic logs, neutron, density, total porosity, water saturation and gamma radiation.

DATA CLASSIFICATION BASED ON DIFFERENT ZONES OF THE RESERVOIR

The results confirm that it seems all data available on total reservoir do not follow the same trend. So it was decided that the data should be divided into several sections, and for each section, creating a separate network, and permeability in each sector is estimated based on a separate network. In this method, the data classification is based on the boundaries of the reservoir zone.

According to the field, the zone classification is based



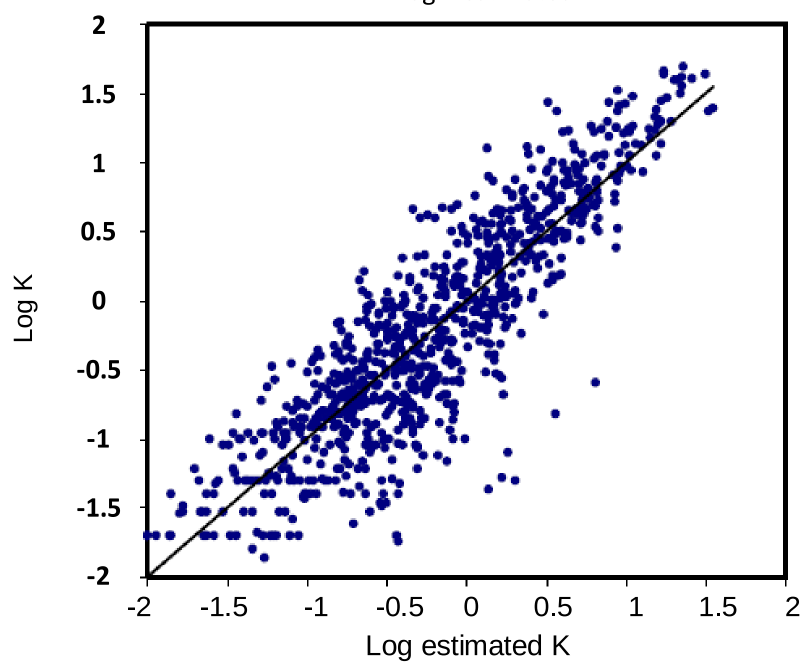


Figure 2. Log core permeability vs. Log permeability estimated by linear regression method (left) and non-linear regression method (right).

Table 1. Performance of each of the networks created for different zones.

Net name	A	B	C	D	E	F	G	H	I	J	K
Zone included in each net	2-1	2-2	3	4-1	4-2	4-3	5	6-1	6-2	7	8 and 9
Train data	0.941	0.927	0.893	0.864	0.82	0.88	0.79	0.783	0.796	0.845	0.775
Test data	0.852	0.755	0.840	0.809	0.80	0.65	0.72	0.733	0.707	0.786	0.731
Validation data	0.890	0.873	0.850	0.833	0.81	0.66	0.76	0.757	0.750	0.803	0.752

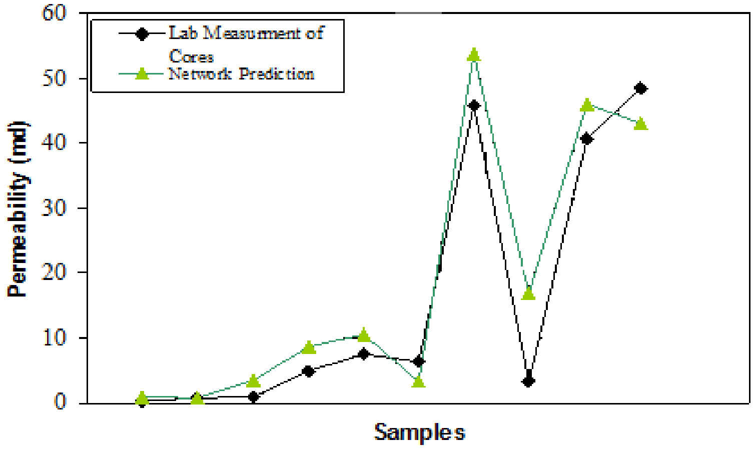


Figure 3. Permeability values predicted by using neural network Compared with values measured in the laboratory in subsection 2-1.

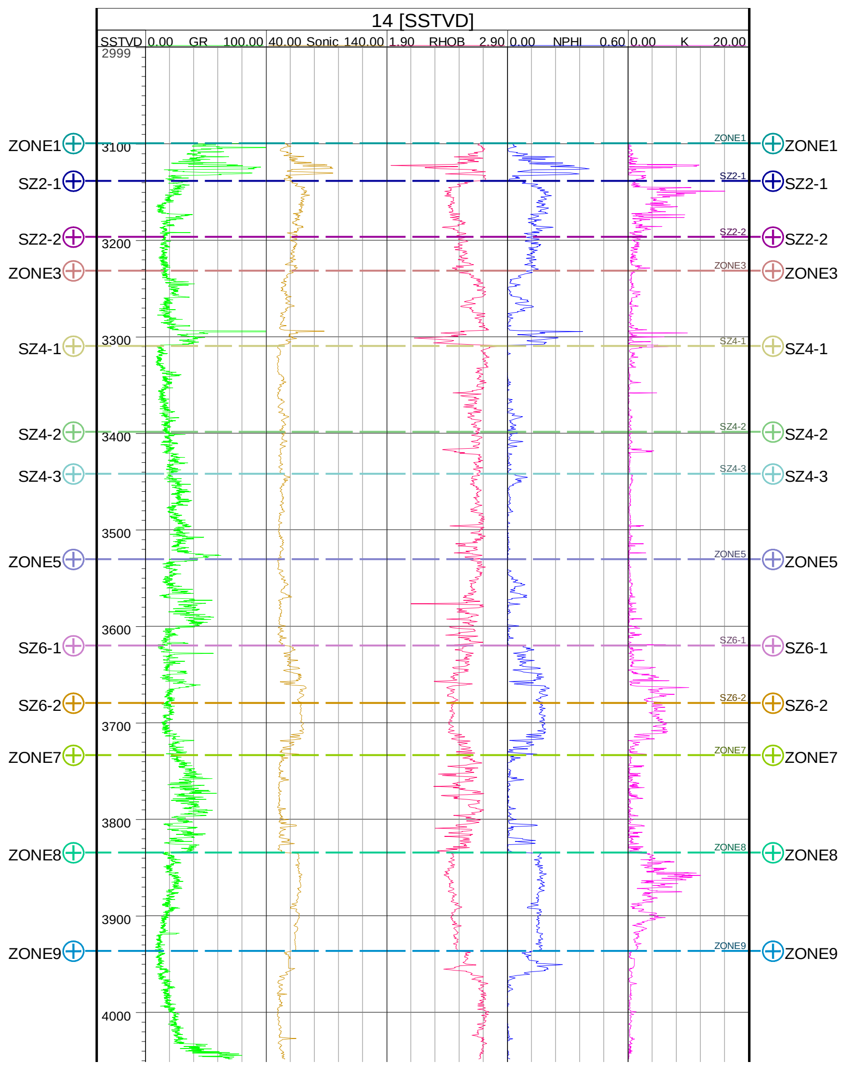


Figure 4. Permeability values calculated by the neural network using logs data performance.

on the porosity of the rock and shale existence, we use the same method for our classification (Table 1 and Figure 3).

According to the results of networks obtained in the previous section, the permeability can be estimated with high accuracy from the log data (Figure 4). If we specified intervals with high permeability, we reached the conclusion that zones 2, 6 and 8 are with high permeability and this is exactly confirm in this field studies.

Conclusion

In general, the results are summarized in to the following:

1. The method provided to train, test, and validation the dataset has shown a good accuracy and suitability for estimating the permeability and network flow.
2. Also, the results obtained from this study showed that the use of neural network for permeability estimation using the log data is possible and neural network model was used successfully to predict permeability.
3. The graphs shown presents the correlation coefficient and the mean absolute error obtained from the neural networks computation and are better defined by the regression analysis result.
4. Unlike experimental approaches, series of specific conditions such as residual water saturation existing in the reservoir are used as initial input, on the other hand, the neural network models has no initial condition. In fact, a neural network model is free of any structure for a predetermined condition.
5. The delineation of zones having low permeability or high is better resolved by the neural networks technique compared to the conventional method.

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