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Estimation of Spatial Distribution of Porosity by Using Neural Networks Method in One of Oil Fields in South of IRAN

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Abstract: The aim of this study is to describe Artificial Neural Networks (ANN) approach that can be used to estimate spatial distribution of porosity in one of oil fields in south of Iran. However coring and well logging are expensive and time consuming, in study of an oil field porosity distribution, both of them have been useful. Firstly, pre-statistical analysis has been presented; secondly the estimation space has been determined, and then the appropriate neural network according to the 21 wells data which 18 of them used for training and the rest for test has been built. Finally, the spatial distribution of porosity in the estimation space has been modeled and the final results of neural network for a random section in some membership levels have been presented.

Key words: artificial neural networks; estimate; spatial distribution; porosity.

INTRODUCTION

Reservoir estimation is a process for quantitatively assigning reservoir properties, such as porosity, permeability, and fluid saturations, while recognizing geologic information and uncertainties, in spatial variability. The estimation of reservoir characterization is in reservoir modeling and simulation and any primary and/or enhanced recovery design process in the petroleum and natural gas industry (Mohaghegh *et al.,* 1996).

Artificial neural networks are parallel-distributed information processing models that can recognize highly complex patterns within available data. In recent years, neural network use has gained popularity in petroleum applications El-Sayaed A. Osman (2004). Artificial neural networks are an information processing technology inspired by the studies of the brain and nervous system. In other words, they are computational models of biological neural structures. Each NN generally consists of a number of interconnected processing elements (PE) or neurons grouped in layers. Fig. 1 shows the basic structure of a three layer network: one input layer, one hidden layer, and one output layer. The neuron consists of multiple inputs and a single output. Input is the values of the independent variables and output is the dependent variables. Each input is modified by a weight, which multiplies with the input value. The input can be raw data or output of other PE's or neurons. With reference to a threshold value and activation function, the neuron will combine these weighted inputs and use them to determine its output. The output can be either the final product or an input to another neuron Al-Fattah S.M, Startzman R.A (2001).

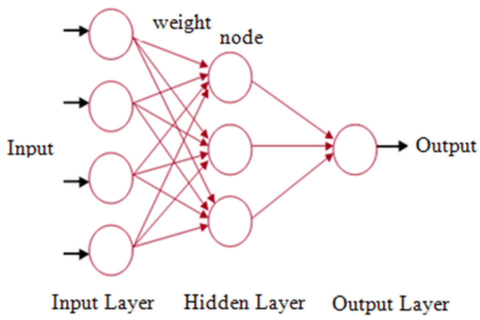

Fig. 1: Basic Structure of a three-layer back-propagation neural network Al-Fattah S.M, Startzman R.A (2001).

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Estimating rock porosity and its spatial distribution in a heterogeneous reservoir is a problem with no direct and known solution. To date, there are only two generally reliable ways of acquiring information on rock porosity, these are laboratory measurements and well test interpretation. Laboratory measurement of porosity from cores obtained from the field or core archives, generally provides reliable values of porosity that can be used in reservoir simulation studies as well as any other design and development studies on a field. The second method for porosity determination is pressure transient analysis, which provides a volumetrically averaged porosity for the volume of the reservoir that has been investigated during the test. It should be noted that during the well testing procedure the length of the test is an important issue. Tests should be designed so that they are long enough to achieve reliable and usable data. On the other hand, the longer the test time, the larger the volume represented by the calculated porosity (Mohaghegh *et al.,* 1996).

In this paper, a new method for porosity estimation is introduced. This technique is quite inexpensive. It does not require production interruption (as in well testing) and provides porosity values that are comparable to those obtained by laboratory measurements of cores. In a feasibility study on this method of porosity prediction/estimation, it was shown that such efforts are indeed fruitful Mohaghegh, S., Arefi, S., (1995). In that study, it was demonstrated that with a limited number of data, a carefully designed and developed artificial neural network can provide acceptable results.

2) Artificial Neural Networks:

Artificial neural networks (ANNs) were developed to model the human brain. Even an ANN fairly simple and small in size when compared to the human brain, has some powerful characteristics in knowledge and information processing due to its similarity to the human brain. Therefore, an ANN can be a powerful tool for engineering applications. The first studies on ANN are supposed to have started in 1943. McCulloch and Pitts defined artificial neurons for the first time and developed a neuron model as in Fig. 2. McCulloch and Pitts network formed the basis for almost all later neural network models (Sarıdemir *et al.,* 2008).

Afterwards, as a second hit, in 1958 Frank Rosenblatt devised a machine called the perceptron that operated much in the same way as the human mind. Rosenblatt's perceptrons consist of "sensory" units connected to a single layer of McCulloch and Pitts neurons. Rumelhardt derived a learning algorithm for perceptron networks with constituted hidden units. Their learning algorithm is called back-propagation and is now the most widely used learning algorithm. Fig. 3 is shown a typical architecture of a multilayer perceptron neural network with an input layer, two hidden layer and one output layer. As a result of these studies, together with the developments in computer technology, use of ANN has become more efficient after 1980 (Sarıdemir *et al.,* 2008).

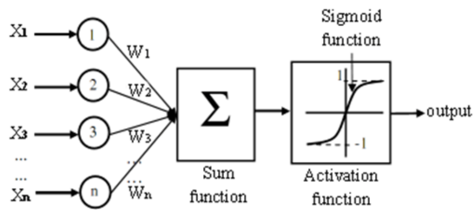


Fig. 2: Simple neuron model (Seginer *et al.,* 1994).

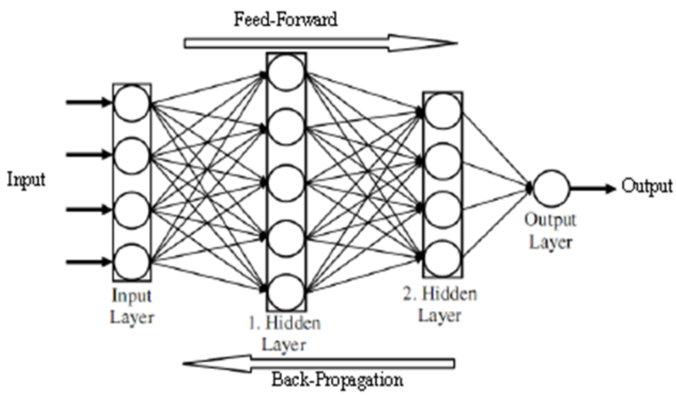


Fig. 3: A typical architecture of a multilayer perceptron neural network (Samanta B, Bandopadhyay S., 2009).

As it can be seen from Fig. 2 an artificial neuron is composed of five main parts: inputs, weights, sum function, activation function and outputs. Inputs are information that enters the neuron from other neurons of from external world (Sarıdemir *et al.,* 2008). Weights are values that express the effect of an input set or another process element in the previous layer on this process element. Sum function is a function that calculates the effect of inputs and weights absolutely on this process element. This function computes the net input that comes to a neuron. The weighted sums of the input components (net)j are calculated using (Eq. 1) as follows (Sarıdemir *et al.,* 2008):

$$(net)_j = \sum_{i=1}^{n} w_{ij} x_i + b \tag{1}$$

Where (net)j is the weighted sum of the jth neuron for the input received from the previous layer with n neurons, wij is the weight between the jth neuron in the previous layer, xi is the output of the ith neuron in the previous layer. b a fix value as internal addition and Σ represents sum function. Activation (transfer) function is a function that processes the net input obtained from sum function and determines the neuron output (Sarıdemir *et al.,* 2008). So, an activation function acts on the value returned by the input function. An input function combines the input vector with the weight vector to obtain the net input to the processing element given a particular input vector. Each of the activation functions introduces a nonlinearity into the neural network, enriching its representational capacity Al-Fattah S.M, Startzman R.A (2001). In fact, it is the nonlinearity of the activation function that gives a neural network its advantage over conventional or traditional regression techniques. There are a number of activation functions. Among those are Sigmoid, arctan, sin, linear, Gaussian, and Cauchy Al-Fattah S.M, Startzman R.A (2001). In general for multilayer feed-forward models as the activation function sigmoid activation function is used (Sarıdemir *et al.,* 2008). It squashes and compresses the input function when it takes on large positive or large negative values. Large positive values asymptotically approach 1, while large negative values are squashed to 0 Al-Fattah S.M, Startzman R.A (2001). The output of the jth neuron (out)j is computed using (Eq. 2) with a sigmoid activation function as follows (Sarıdemir *et al.,* 2008):

$$(out)_j = f(net)_j = \frac{1}{1+e^{-\propto (net)_j}} \tag{2}$$

Where ∝ is constant used to control the slope of the semi-linear region. The sigmoid nonlinearity activates in every layer except in the input layer. The sigmoid activation function represented by (Eq. 2) gives outputs in (0, 1). If it desired, the outputs of this function can be adjusted to (1, 1) interval. As the sigmoid processor represents a continuous function it is particularly used in non -linear descriptions. Because its derivatives can be determined easily with regard to the parameters within (net)j variable (Sarıdemir *et al.,* 2008).

3) Neural Network Model Structure and Parameters:

There are a number of design factors that must be considered in constructing a neural network model. These considerations include the selection of neural network architecture, the learning rule, the number of processing elements in each layer, the number of hidden layers, and the type of transfer function Al-Fattah S.M, Startzman R.A (2001). ANN model is carried out in this research has three neurons in the input layer and one neuron in the output layer as demonstrated in Fig. 4. Two hidden layer with six and four neurons were used in the architecture of multilayer neural network due to its minimum absolute percentage error values for training and testing sets. The neurons of neighboring layers are completely interconnected by weights. Finally, the output layer neurons produce the network prediction as a result.

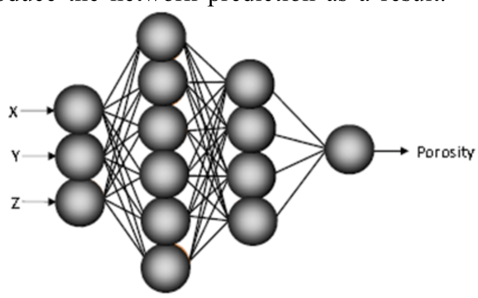


Fig. 4: The system used in the ANN model.

In this study, the back-propagation training algorithm has been utilized in feed –forward two hidden layers. Back-propagation algorithm (Bogdan M. Wilamwski, 2009), as one of the most well-known training algorithms for the multilayer perceptron, is a gradient descent technique to minimize the error for a particular training pattern in which it adjust the weights by a small amount at a time (Sarıdemir *et al.,* 2008). On the minus side, back-propagation (BP) algorithm is very slow and requires 100-1000 times more interactions than the more advanced algorithms such as levenberg-marquardt (LM), or neuron by neuron (NBN), algorithms (Bogdan M. Wilamwski, 2009). What is most important is that the BP algorithm is not only slow but often it is not able to find solutions for close-to-optimum neural networks (Bogdan M. Wilamwski, 2009); consequently, in this study, the LM training algorithm has been utilized in feed-forward two hidden layers. The non-linear sigmoid activation function was used in the hidden layer and the neuron outputs at the output layer. Learning rate values were determined and the model was trained through iterations. The trained model was only tested with the input values and the estimated results were close to experiment results. The values of parameters used in neural network model are given in Table 1.

Table 1: The values of parameters used in neural network model.

Parameters	ANN
Number of input layer units	3
Number of hidden layer	2
Number of first hidden layer units	6
Number of second hidden layer units	4
Number of output layer units	1
Learning rate	0.78
Error after learning	0.000030

4) Field data:

A data bank containing a large number of data points was compiled over a wide range of reservoir porosity. The data have been gathered from a typical Asmari oil reservoir in south-west of Iran. While most of the porosity data are obtained from core analysis under reservoir conditions in the laboratory, data, which are obtained from well testing method, are also included in the data bank.

It has been a fairly common practice to present porosity data vs. X, Y and Z (depth) of the reservoir in order to generate a correlation between these variables. The variations of composition porosity of this formation with X, Y and Z are shown in Figs. 5 to 7, respectively. The data are very scattered and no obvious trend can be observed in these plots.

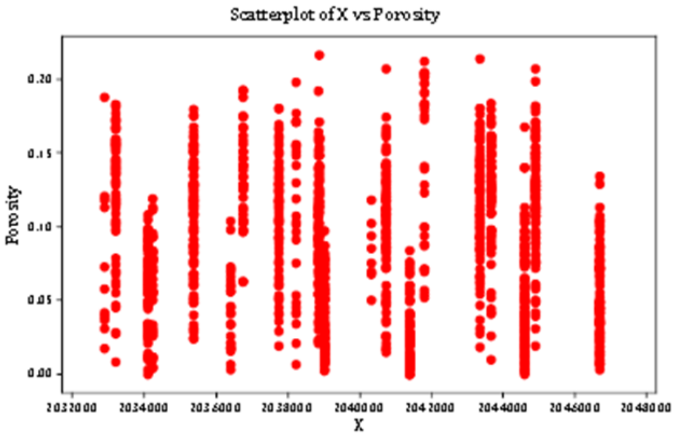


Fig. 5: Variation of porosity with X for composite data.

5) Data Processing, Determination of Block Dimensions and the Estimation Space:

We have only data which comes from wells in the oilfield in west of Iran. The space between each sample starts from 4.6 m to several meters, but the average of this space is about 2m which has been analyzed as a sample of probable porosity.

The histogram of porosity data, after compositing, has shown in fig. 8. As we can see the distribution of porosity is almost normal and it does fulfill the basic assumption of the estimation process. So by considering the type of porosity distribution, we used normal method.

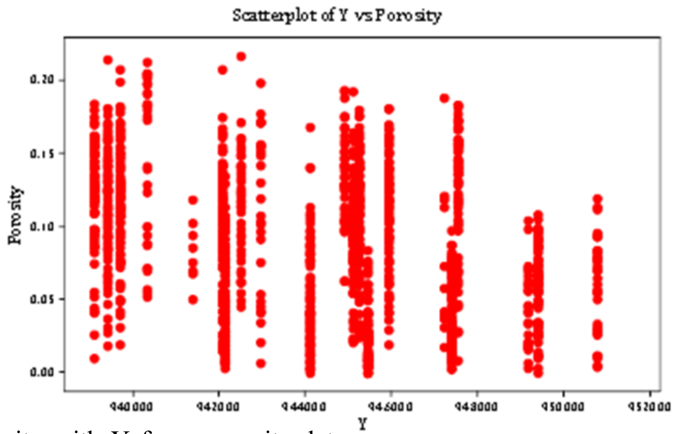


Fig. 6: Variation of porosity with Y for composite data.

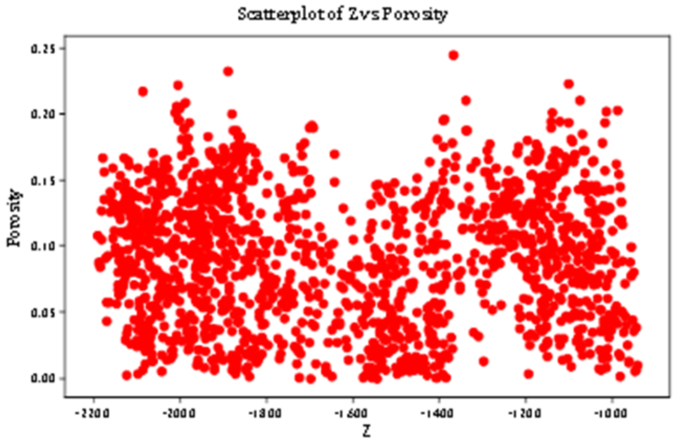


Fig. 7: Variation of porosity with Z (depth) for composite data.

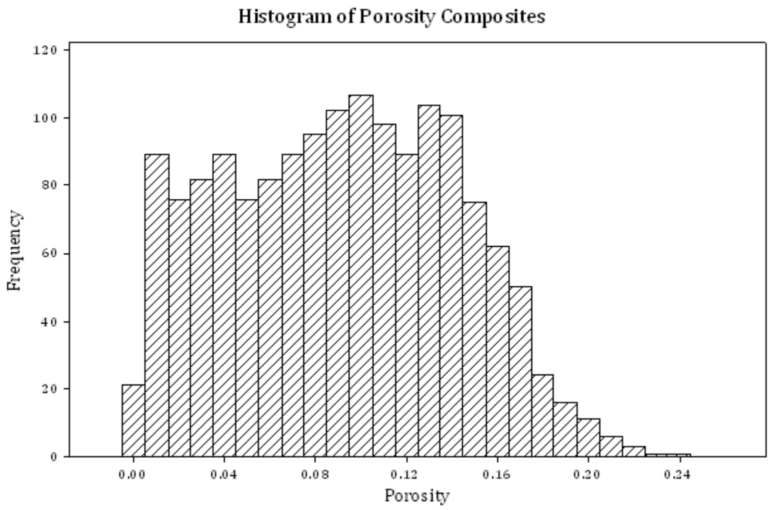


Fig. 8: The histogram of porosity data after compositing.

Different parameters influenced on the dimension of the estimation blocks such as disperse of the porosity all over the reservoir, the condition of production planning according to the available equipments and tools. The blocks thickness determined by considering the populations of effective porosity and ineffective porosity vertical thickness. In this study, the horizontal dimension of blocks determined 500 m × 500 m and 2 m for the blocks thickness, according to the effective porosity and ineffective porosity vertical thickness distribution.

6) the Spatial Distribution of Porosity in the Estimation Space:

After training, testing and evaluating the ANN as an estimator it can estimate the porosity in the new coordinate space. Estimated value of spatial distribution of porosity in each block of horizon is a plan drawing. For example the plan No. 310 (−1581 m) is a result of spatial distribution of porosity, has shown in fig. 9. The results are as following:

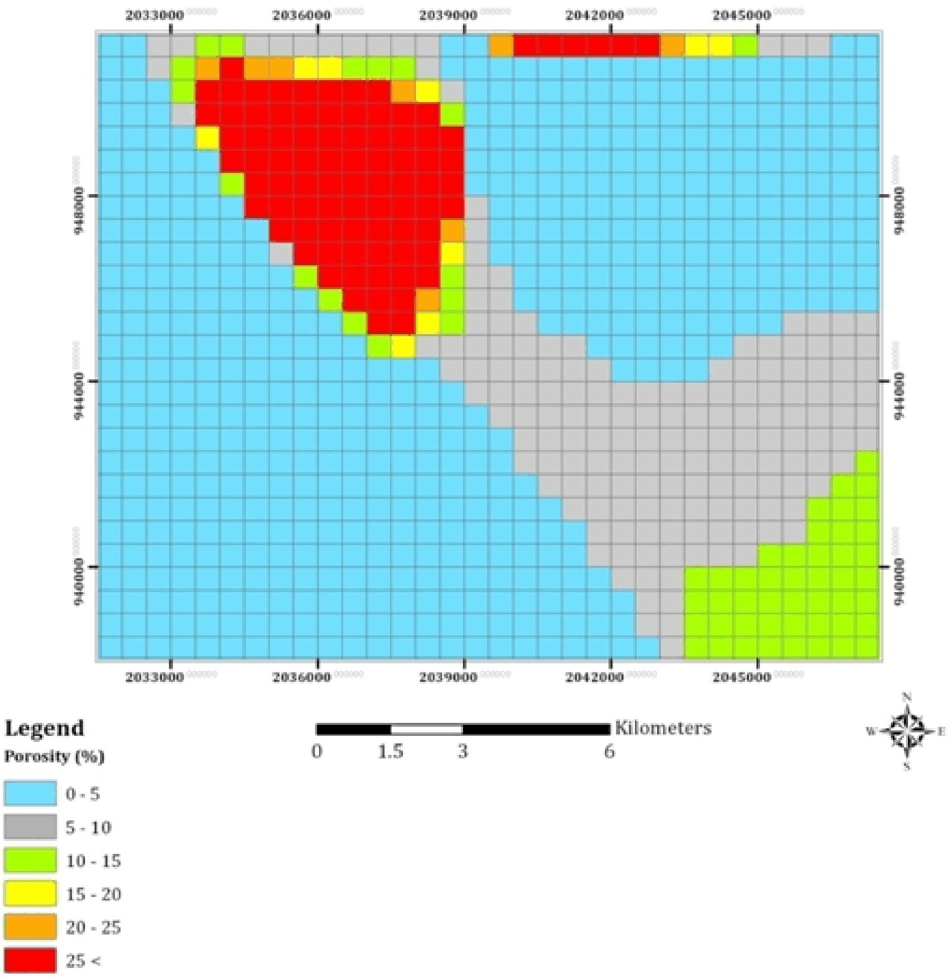
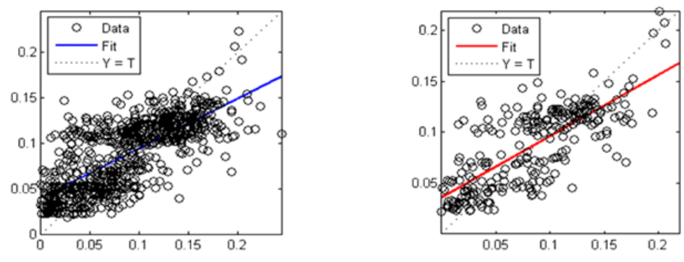


Fig. 9: The plan of estimated porosity by ANN for No. 310 (-1581 m).



ANN regression for training, R= 0.78 ANN regression for testing, R= 0.80

Fig. 10: The regressions between the wells data and the estimated values.

- More than 25 % porosity are shown with red color blocks that are perfect site for collection of hydrocarbon and economic product.
- Between 25 % to 20 % porosity are shown with orange color blocks that are very good site for collection of hydrocarbon and economic product.
- Between 20 % to 15 % porosity are shown with yellow color blocks that are good site for collection of

hydrocarbon and economic product.

- Between 15 % to 10 % porosity are shown with green color blocks that are conducive site for collection of hydrocarbon and economic product.
- Between 10 % to 5 % porosity are shown with grey color blocks that are poor site for collection of hydrocarbon and economic product.
- Less than 5 % porosity is shown with blue color blocks that are very poor site for collection of hydrocarbon and economic product.

In each horizon of study area we should pursue red, orange, yellow and green color blocks because of their potential of economic production.

Conclusions:

The following conclusions were reached during this study:

1. This investigation shows that the perceptron neural network architecture is capable of estimating formation porosity using laboratory measurement of the cores and the well testing data attained from the field.
2. An innovative methodology for test data selection was developed which significantly enhanced the ability of the neural networks for porosity estimation.
3. The neural network model structure that produces minimum error on calibration data is expected to acquire the generalization property, as the calibration data set acts as an independent observer in supervising the generalization property of the model .Finally, the actual predictability of the model is tested on the validation data set (Samanta B, Bandopadhyay S., 2009).
4. One way to achieve improved generalization capability, which was adopted in this study, is to train the network using training data and to test the network using testing data and to observe its performance on calibration data.
5. Data vectors were divided into two sets using random indices, 1300 for training and 249 for testing.
6. Regarding to the regression between estimated and real values in ANN technique (Fig. 10), it seems that the R parameter in these regressions is a good criteria for estimating the porosity distribution in this oilfield in south of Iran.
7. A complete description of reservoir model was obtained by combining neural networks estimations of porosity (and other physical parameters of reservoir) from coring and well log data.
8. Based on the results from Fig. 9, we can see that the areas including red, orange, yellow and green blocks are important for the economic production.

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