# 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.*

**Keywords:** *artificial neural networks; estimate; spatial distribution; porosity.*

## 1.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 [9].

ANNs 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 [5]. Many authors discussed the applications of neural network in petroleum engineering [10]. ANNs 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. 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. The output can be either the final product or an input to another neuron [1].

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 [9].

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 [10]. In that study, it was demonstrated that with a limited number of data, a carefully designed and developed ANN can provide acceptable results.

## 2. 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 [1]. 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. 1.** 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.

Error-back propagation (EBP) algorithm [3], 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 [21]. On the minus side, EBP 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 [3]. What is most important is that the EBP algorithm is not only slow but often it is not able to find solutions for close-to-optimum neural networks [3]; 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.**

## 3. Data processing, determination of block dimensions and the estimation space

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

The histogram of porosity data, after compositing, has shown in **fig. 2.** 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.

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 $500\ m \times 500$ m and 2 m for the blocks thickness, according to the effective porosity and ineffective porosity vertical thickness distribution.

## 4. The spatial distribution of porosity in the estimation space

After training, testing and evaluating the neural network 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. 3.**

## 5. 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. Data vectors were divided into two sets using random indices, 1300 for training and 249 for testing.
3. Regarding to the regression between estimated and real values in ANN technique (**Fig. 4)**, 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.
4. Based on the results from **Fig. 3**, we can see in each horizon of study area we should pursue red, orange, yellow and green color blocks because of their potential of economic production.

## 6. Acknowledgments

This article is dedicated to the silent nights of my beloved father *Mohsen Tehrani Majd* who passed away several years ago.

## 7. References

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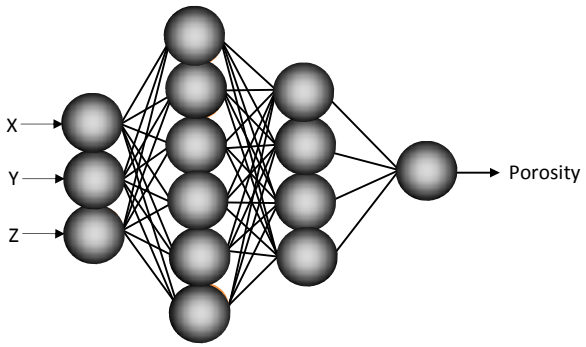



**Fig. 1-The system used in the ANN model**.

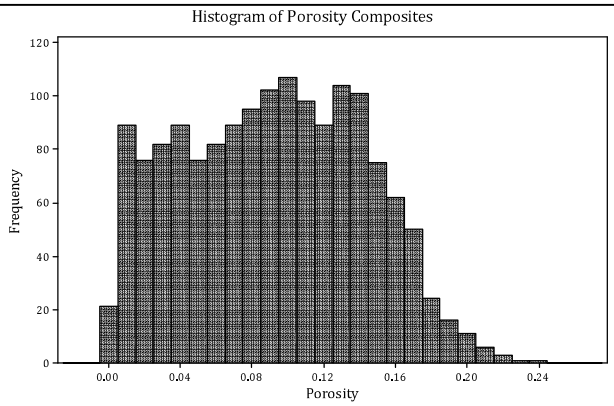



**Fig. 2-The histogram of porosity data after compositing.**

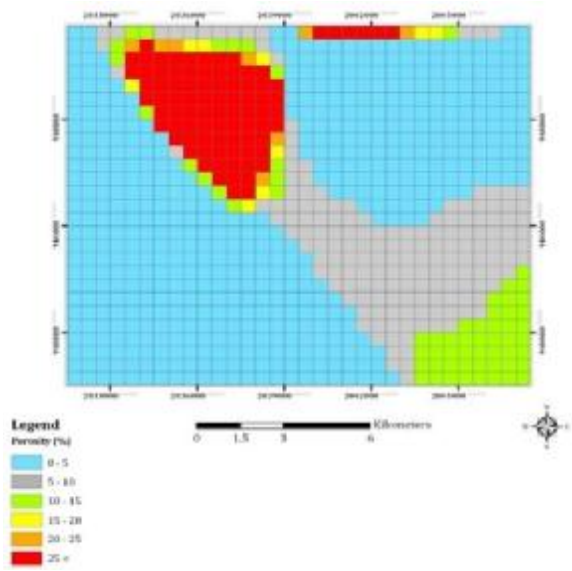
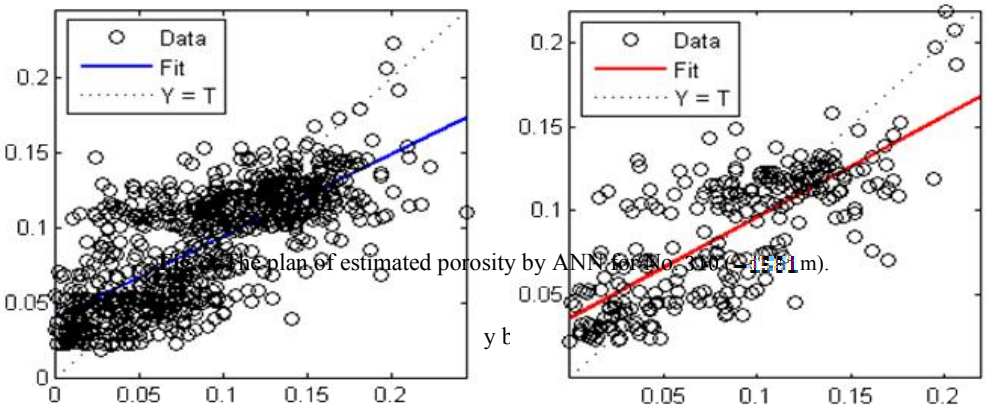



Fig. 3- The plan of estimated porosity by ANN for No. 300 (-1581m).




ANN regression for training, R= 0.78

ANN regression for testing, R= 0.80

**Fig. 4- The regressions between the wells data and the estimated values.**

**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 |