



2528-9705



## Determination of Effective Porosity using Seismic Attributes in Mansouri Pil Field

Sara Vashaghian<sup>1\*</sup>, Ezatallah Kazemzadeh<sup>2</sup>, Majid Nabi Bidhendi<sup>3</sup>, Iraj Madahi<sup>4</sup>

<sup>1</sup>Department of Geophysics, Faculty of Basic Sciences, North Tehran Branch, Islamic Azad University, Tehran, Iran.

<sup>2</sup>Research institute of petroleum industry Department of Geophysics Islamic Azad University Science and Research Branch Tehran, Iran.

<sup>3</sup>Department of Geophysics, Institute of Geophysics, University of Tehran, Iran.

<sup>4</sup>Communication with industries and research center of Research Institute of Petroleum Industry.

**\*\*Correspondence author:**

Email: [saravashaghian@gmail.com](mailto:saravashaghian@gmail.com)

### ABSTRACT

The current research is focused on the Asmari reservoir in one of Iran's oil fields. Integration of well logs and seismic data is a main goal of geophysicists. Likewise, one of the most significant petrophysical parameters is effective porosity prediction, which plays a very important role in the oil and gas industries. Effective porosity is predominantly significant from the point of view of petroleum geology and exploitation engineers; consequently, in this study, the researchers examine effective porosity. In the research method used in this project, first, via seismic data inversion, the acoustic impedance attribute is extracted. By applying mathematical relations to it and other seismic characteristics with well logs, the parameters of the reservoir porosity at the well site are estimated and then extended to the seismic data range. Lastly, their lateral and vertical changes were checked. The current study was done in a hydrocarbon anticline, and the effective porosity of the source rock was estimated using common seismic attributes. The examined methods for porosity estimation are single and multi-attribute methods and neural networks. The PNN algorithm uses well logs in the training phase to estimate reservoir properties. The results of the porosity estimation in the single and multiple attributes and neural network methods have been compared. Compared to the other two methods, the use of the neural network method has resulted in less error in estimating the effective porosity. This study has revealed that the neural network application effectively predicts porosity.

**Keywords:** Mansouri oil field, Seismic attributes, Porosity, Neural networks.

## INTRODUCTION

Estimating porosity and saturation values in the oil industry is typically limited to the wells location and the surrounding areas. It is continuously tried to achieve precise porosity estimation and saturation values in the whole area of the reservoir. Regarding its extensive lateral coverage and low costs compared to other methods of obtaining data and subsurface information, seismic data is of special prominence in mapping the subsurface properties of hydrocarbon fields and reservoirs (Khoshdel, 2006).

Based on the current restriction in generalizing the reservoir characteristics obtained from several wells to the surrounding areas, using seismic data and indirect methods in estimating and generalizing rock and fluid reservoir parameters and determining their range and changes in the extent and volume of the reservoir become very significant. So that the volumetric models

of the parameters estimated from the seismic characteristics can be used as the initial input of the static modeling stage of the reservoir (Badley, 1985), and by decreasing the modeling calculations repetition, it causes a reduction in the new drillings risk and as a result reduction of costs related to the development and increase of extraction from the reservoir studied in this project. The Hampson Russell software is selected to conduct this research (Tahmasabi Abder, no date).

The data from the Mansouri field is used to do this research. Along with its interpretation and processing reports and the data of several wells and their related reports, the data the researchers comprise the three-dimensional seismic data of the field. In the beginning, after studying the accessible reports, the well-log data was checked. Then necessary possible corrections are made. The current study uses the data of several wells with different logs such as porosity, acoustic, impedance, etc. (Brown, Jan-Feb 2001). In the next stage, these data are called in the software, and on the other hand, the 3D seismic information is also called in the software. Next, the well logging data (sonic, density, and porosity diagrams) are converted with the help of well seismic data (Check Shot) to synchronize with the seismic data in time instead of depth, and a synthetic map is made with the help of that earthquake. Then acoustic and density logs will be used to make synthetic seismic maps and correlate them with seismic horizons and seismic inversion. Afterward, the well or seismic data should be calibrated (Gasem al-Asgari, 2004). The acoustic impedance model is organized in the next stage via seismic inversion. It is essential to attain a model with the least error by repeating the modeling with different parameters. This model improves vertical resolution and reveals reservoir layers (Sherrif, Geldart, 1999). In the next section, considering that acoustic impedance is usually closely related to reservoir properties (such as porosity) (Sabouhi, no date), in this research, it will be used to obtain reservoir properties; in this way, the relationship between effective porosity and sound impedance at the location of the wells is extracted and generalized to the field with the help of the model. The inversion method used in this project is based on the model first introduced by Kirk and Schneider in 1983. The reason for selecting this method is that the method based on the model treats the ground in the form of acoustic impedance blocks, and this method is more sensitive than the return methods to the initial model and wavelet all at once; this method has very little sensitivity to noise, and it is more sensitive to wavelet changes. The petrophysical parameters of the reservoir play a vital role in knowing the characteristics of the reservoir; in this study, the estimation of effective porosity and objects is examined among the petrophysical parameters.

### **Geological and geophysical description of Mansouri field**

The Mansouri (Asmari) oil field is located in the northern Dezful subsidence area, about 60 km south of Ahvaz, and has several reservoir formations. The Mansouri oil is located 45km southeast of Ahvaz, and it is located in the vicinity of the Abteymour field from the west and Shadgan field from the northeast. The length of the field at the contact surface of Taft water is about 39 km, and its width is about 3.5 km; the extension of this field, like most of the fields in the Zagros region, is in the northwest-southeast direction (Hazineh, no date). So far, 58 wells have been drilled in this field, most of them with the aim of production from the Asmari reservoir, and some of them have been drilled in different zones of the Bangistan group. According to the maps



attained from seismographic studies and underground construction maps, the Mansouri field can be considered an elongated anticline with gentle and low slopes in the northwest and southeast direction (Alizadeh Pirzaman, 2010).

In the current study, the relationship between the porosity log and several seismic attributes using the artificial neural network method is one of the non-linear methods used to achieve the relationship between the porosity log and the seismic attributes using probabilistic artificial neural networks. This is done in two ways: First, the network automatically processes and uses the number of attributes. In the second method, it uses the results of porosity estimation by several seismic attributes. Here the researchers use the second method to create a neural network. All neural networks work well when doing the interpolation, but typically they do not answer very well when doing extrapolation (Elog Modul, Hampson-Russell., 2006). One of the solutions to this problem can be removing the trend and using neural networks in the residual prediction. This selection is embedded in the “Transform Cascading With The Multi-Attribute Trend From” option of the emerging program. By selecting this option, we will have the following:

- Calculation of multiple attributes using the same attributes and the same operator length in the neural network.
- Prediction of each target graph using trained seismic attributes.
- Smoothing the projected images using the Smooth Length available in the next field on this window.
- Subtraction of the predicted Smooth images from the original target images.
- Neural network training using residual information from subtraction.



## Findings

### Porosity estimation

To estimate the porosity, a relationship should be found between the produced acoustic impedance and the porosity pattern at the well site and different seismic attributes. This relationship can be in the form of a simple linear relationship that is obtained by using one attribute or several attributes, or it can be obtained from non-linear relationships such as using neural networks.

### Collecting the data needed to estimate porosity

To estimate porosity, it is necessary to have seismic data at the well site. These data are the same 3D seismic data collected in the Mansouri field. Several seismic traces near the well site were averaged to extract different seismic attributes on this trace. An external attribute, the acoustic impedance produced in the previous stage, is averaged at the well location. Similarly to the

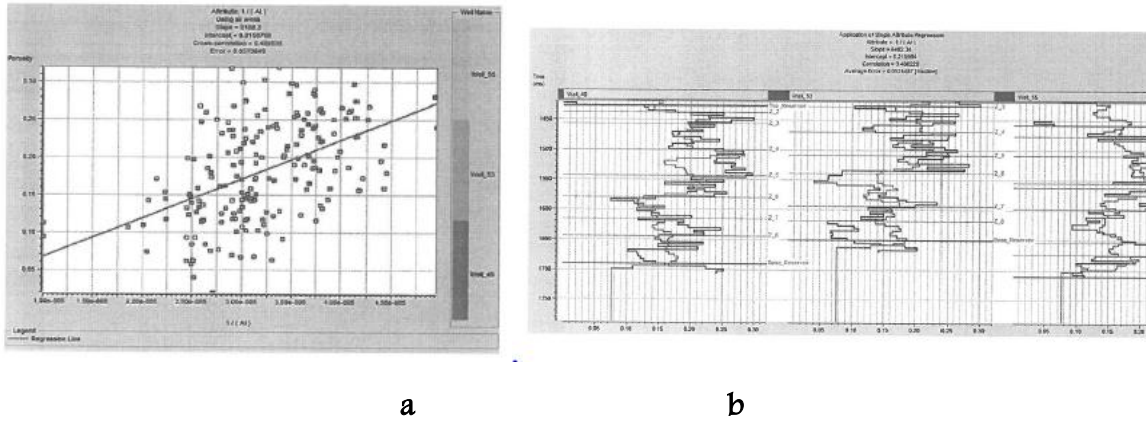
seismic data on this seismic trace, different attributes are extracted. Finally, one of the following methods is used for the relationship between the acoustic log and various attributes.

### Methods used to obtain a relationship between the porosity log and different seismic attributes

Linear or non-linear relationships can be used to attain a relationship between the porosity log and various seismic attributes. The linear regression method can establish the existing linear relationships between one attribute with a porosity pattern or several attributes with a porosity pattern. Non-linear relationships can include neural networks (Hampson, 2001).

#### 1. Attaining the relationship between the porosity log and a single seismic attribute

To this end, cross-plots can be drawn between the porosity log and different attributes. The attribute that shows the highest correlation value can be extracted. The porosity value of the entire area can be estimated from the relationship between that attribute and the porosity log. Normally, the porosity pattern displays an acceptable correlation with the inverse of the acoustic impedance (Reynolds, 1997). Figure (2) depicts the relationship between the porosity graph and the acoustic impedance image. As evident in this figure, the correlation percentage between these two parameters is estimated to be around 444.

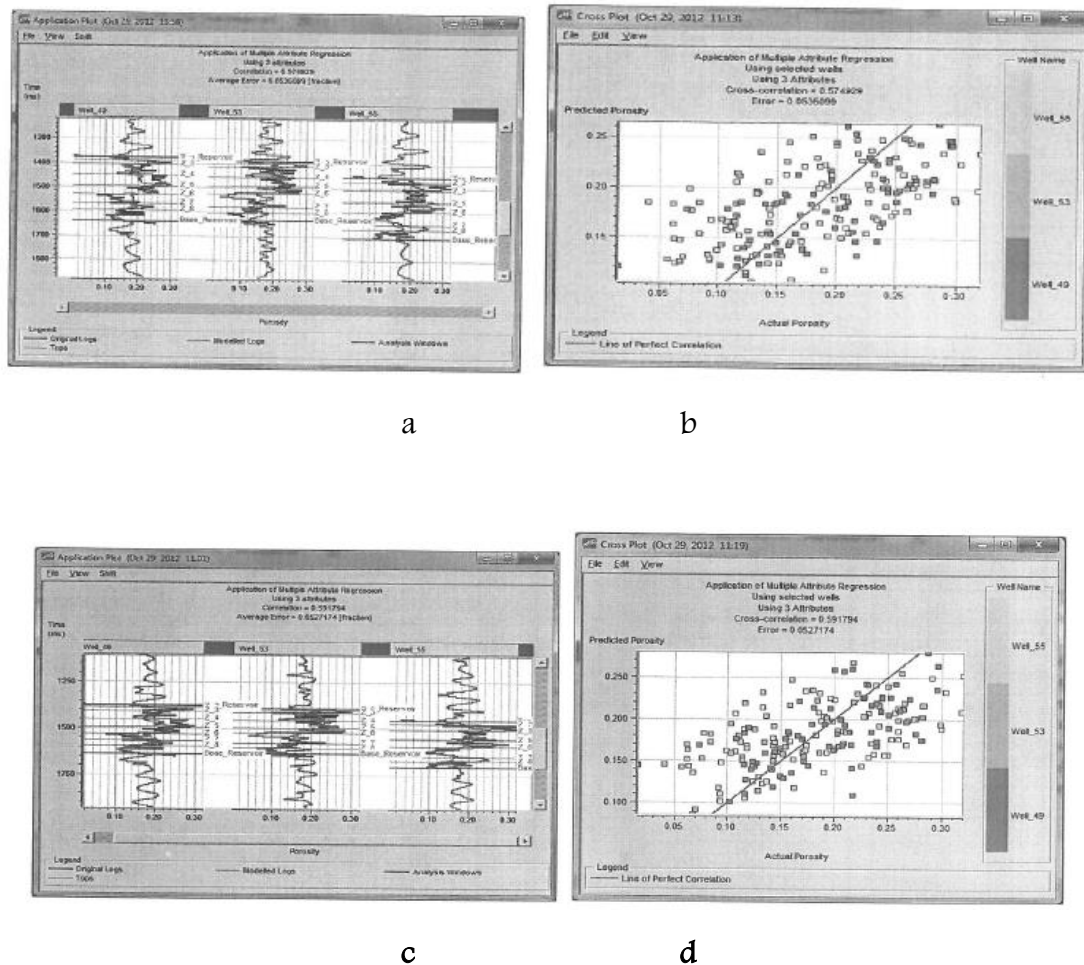


**Figure 1: a)** Relationship between the porosity log and the acoustic impedance image using the single attribute method, **b)** Quantitative result of the estimation at the well site using an attribute

As seen in Figures (1) the researchers are allowed to use the first three attributes; now, the researchers continue the process with two different operator lengths, three and five, using three attributes.

#### 2. Obtaining the relationship between the porosity log and several attributes

One of the methods of estimating the amount of porosity using a non-linear method is using several seismic attributes. This method has good advantages. This means that it upsurges the correlation percentage to a satisfactory level, which should be checked for the precision of this correlation (Validation Error) (Log properties, 1994). When using multiple attributes, it should be noted that the resolution of the attributes is different from the graphs. To avoid this problem, some attribute data is used to estimate the porosity of a plot point, which is done with a number called operator length.



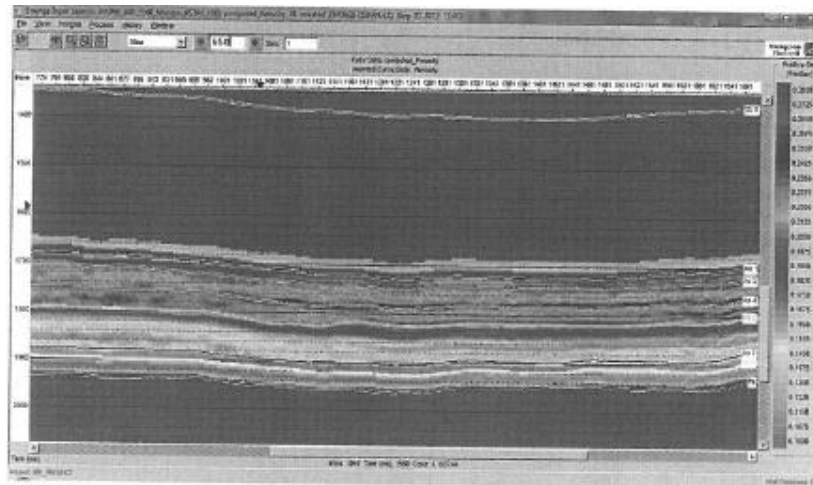
**Figure 2:** a) Correlation value using the first three attributes and operator length 3  
 b) Cross-plot related to the use of three attributes and operator length of three  
 c) Correlation value using first three attributes and operator length five  
 d) Cross-plot related to the use of three attributes and five operator lengths

The results revealed that the use of three attributes gives a good correlation. In using three attributes, the researchers consider the length of the operator to be five because the correlation rate is about 90. (Figure 2)

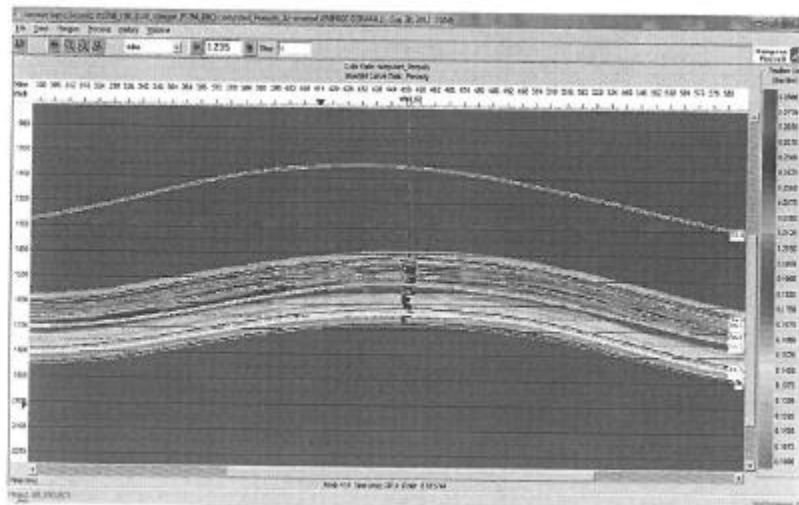


**Result of porosity estimation using extracted seismic attributes**

At this stage, the relationship of seismic attributes between the extracted seismic cube and the target log is applied to the seismic cube to obtain an estimate of the studied field's porosity using the seismic attributes method. .( **Figure 3**)



a



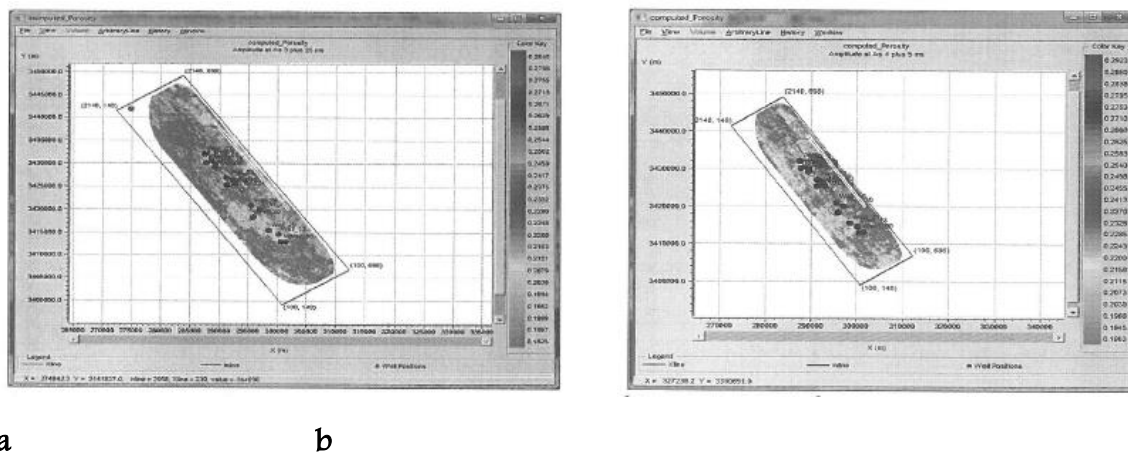
b

**Figure 3: a) Porosity estimation result using seismic attributes in 150 Xline**

**b) Porosity estimation result using seismic attributes in 1245 Inline**

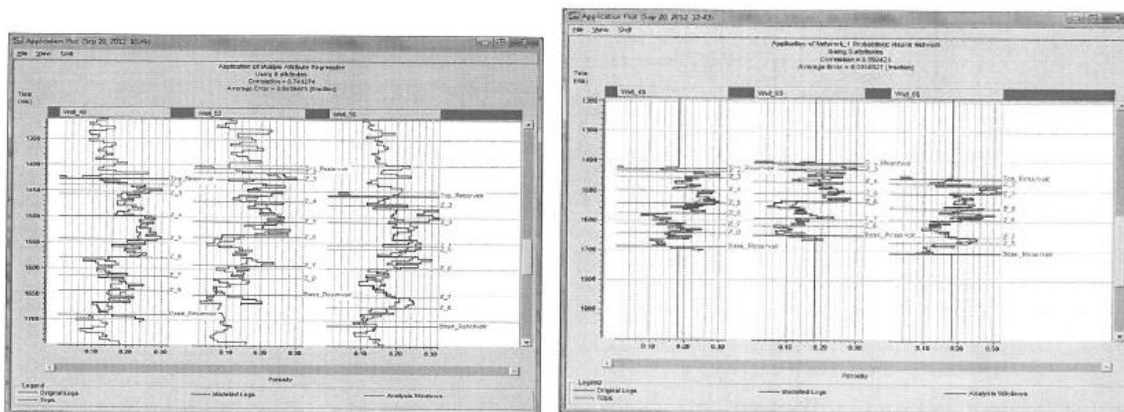
**Result of effective porosity estimation in different zones**

As seen from the above figures, zone 1 has 16-23% porosity, which is in the good to very good category, and this layer is mainly composed of dolomitic lime, lime, and shale limes. Zone 2 is mainly composed of shale sands and calcareous sands and has good, very good, sometimes moderate porosity development and hydrocarbons. Based on the evaluations, this zone has a good reservoir quality compared to other zones. Zone 3 has a porosity development of 13 to 36, and this percentage of porosity is in the very good to a low category, and in the middle part, it is in the form of thick hydrocarbon veins. The porosity in zone 4 to 8 is approximately 12 to 19. In some points, it can be seen that the porosity reaches about 20%, which means that the scope of this part is limited. Since this area is located at the water-oil contact level, this zone has a very small hydrocarbon column. .( Figure 4)



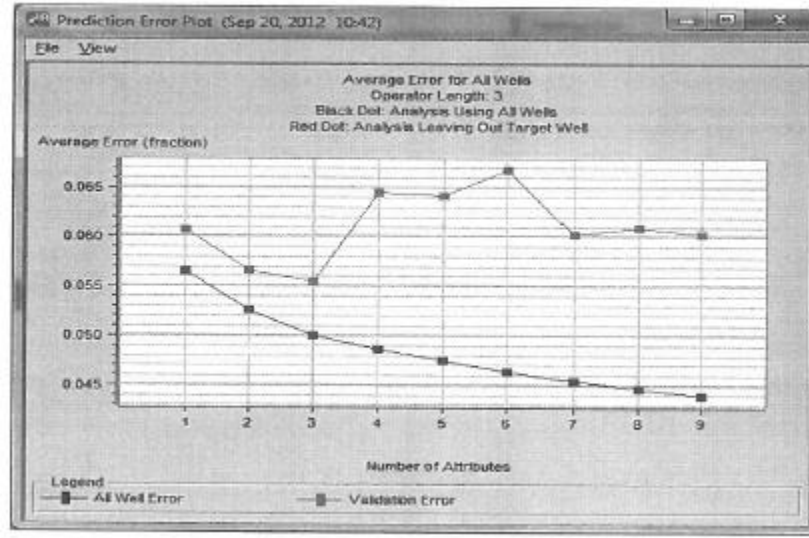
**Figure 4:**a) Estimation of porosity at a time point of 25 milliseconds inside the Asmari Formation 3 using the multi-attribute seismic method, b) Estimation of porosity at a time point of 5 milliseconds inside Mazand Asmari using the multi-attribute seismic method

## 1. Relationship between porosity log and several seismic attributes using artificial neural networks method



a

b

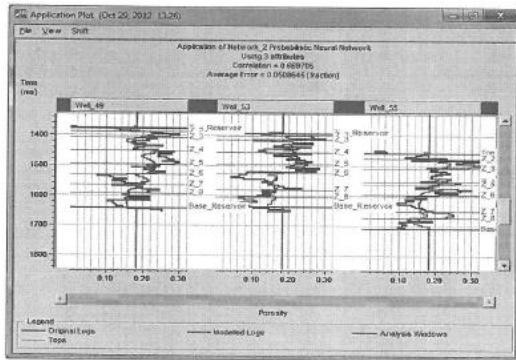


c



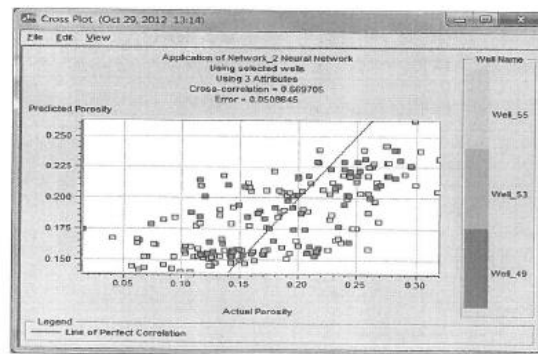
**Figure 5:** a) correlation obtained from the neural network method in porosity estimation with nine attributes and operator length of three training stages, b) Correlation obtained from the neural network method in the palm tree estimation with three attributes and five operator length. c) Correlation value in porosity estimation using nine attributes with operator length 3

As seen in the figure5, the researchehrs are allowed to choose the first three attributes. In other words, the first three attributes have a downward trend, and the Validation Error chart in the first three attributes correlates well with the All Well Error. Both charts have a downward trend, indicating that the researchers are only allowed to choose the first three attributes out of nine.



a

b



**Figure 6:** a) Correlation value obtained from the neural network method in porosity estimation using 34 attributes, b) Cross-plot related to neural network method in porosity estimation using three attributes and operator length



It can be seen in Figure6 that the agreement obtained in the estimation of porosity using the neural network method using three attributes correlates about 17.

table1 shows a comparison of the methods used in porosity estimation.

**Table 1:** Comparison of single-attribute, multi-attribute, and neural network methods in porosity estimation

Method used in porosity estimation	Correlation (percentage)	rate	Error rate (fraction)	
Single attribute	49%		0.0574	
Several attributes (No=3, OI=3)	57%		0.0535	
Several attributes (No=3, OI=5)	60%		0.0527	
Method used in porosity estimation	Training stage		Validation stage	
	Correlation (percentage)	Error (fraction)	Correlation (percentage)	Error (fraction)
Neural Networks (No=3, OI=5)	74%	0.0347	67%	0.0050

As seen in the Table1, porosity estimation by the neural network method gives a good correlation. Consequently, it is better to use the neural network method to estimate the porosity

## Conclusion



In the current study, having the necessary information of the region, it was tried to minimize the error of porosity prediction using seismic attributes using multi-attribute methods and neural networks, and a new approach was introduced in this study. Then, after the interpretation and selection of the desired horizons, the wavelet was obtained using statistical methods and using the wells, and after correlating the well logs with the seismic cube of the Mansouri field, the acoustic impedance model was calculated using the inversion method based on the model. In the wavelet determination phase, it was calculated to be a wavelet with an average correlation of 70% (for synthetic seismic mapping at the location of the mentioned wells in the Mansouri field). With the help of this wavelet, the acoustic impedance was obtained by the inversion method based on the model, and finally, the porosity model was calculated from several methods.

To estimate porosity, the most common method is to use the method of seismic attributes and stepwise regression. Based on the evaluations, it can be seen that the correlation in the multi-attribute method for the operator of length 5 with 60% correlation, and the error rate is 0.052. Compared to the same operator length and using PNN artificial neural networks in the training phase with 74% correlation and 0.034 error rate and the validation stage with 0.67 Correlation and 0.005 error rate, which in terms of Correlation numbers and the obtained error is in a very good position compared to the multi-attribute method

### Recommendations

Obviously, with the numbers achieved from the neural network method, it is recommended to estimate the porosity in the Mansouri field, and the use of these methods will decrease the risk of new drilling and, as a result, reduce the costs related to the development and increase of extraction from the reservoir studied in this project.

**Acknowledgment:** This work was conducted under support from the Research Institute of Petroleum Industry. Also I as a first author offer sincere gratitude to Dr. Ezzat allah Kazemzadeh to prepare well data.

### Conflict of Interest:

Non

### Funding:

Non

### Ethical statements

Non

### References

1. Alizadeh Pirzaman, M.S., 2009, Evaluation of reservoir properties and lithology of Asmari formation in Mansouri oil field, Shahid Chamran University, Faculty of Earth Science

2. Badley, M., 1985, Practical Seismic Interpretation, International human resources development corporation, Boston.
3. Brown, A. R., Jan-Feb 2001, Understanding seismic attributes, Geophysics, Vol. 66, No. 1, pp. - 747,48.
4. Elog Modul, Hampson-Russell., 2006, Theory And Guide.
5. Hampson, D.P., Schuelke, J. S., and Quirin, J. A. Jan-Feb 2001. Use of multiattribute transforms to predict log properties from seismic data, GEOPHYSICS, VOL.66, NO. 1, P.220-236.
6. Hazineh, M., Different methods of seismic wavelet extraction, University of Tehran
7. Khoshdoel, H., 2006, Exploration management of Iran National Oil Company, General Department of Geophysics, 3D data inversion report of Chengole field GR2212, Sanat Naft University
8. Log properties, 1994, Parts 1, 2, and 3 by Schultz et al, The Leading Edge, May, June, and July
9. Qasim al-Asgari, M., R., 2004, Principles of Exploration Geophysics, Aizh Publications, the first edition of autumn
10. Reynolds, J. M., 1997, An introduction to applied and environmental geophysics, John Wiley & Sons
11. Sabohi, M. Porosity in hydrocarbon reservoir
12. Sherrif, R., Geldart, L, 1999, Exploration Seismology, second edition, Cambridge University Press.
13. Tahmasabi Abdar, M., Quantitative description of visible parameters by combining seismic data and charting in one of Iran's oil fields, the University of Tehran, Faculty of Mining Engineering

