# Estimation of Reservoir Porosity Using Seismic Post-Stack Inversion in Lower Indus Basin, Pakistan

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**Abstract:** Seismic post-stack inversion is one of the best techniques for effective reservoir characterization. This study intends to articulate the application of Model-Based Inversion (MBI) and Probabilistic Neural Networks (PNN) for the identification of reservoir properties i.e. porosity estimation. MBI technique is applied to observe the low impedance zone at the porous reservoir formation. PNN is a geostatistical technique that transforms the impedance volume into porosity volume. Inverted porosity is estimated to observe the spatial distribution of porosity in the Lower Goru sand reservoir beyond the well data control. The result of inverted porosity is compared with that of well-computed porosity. The estimated inverted porosity ranges from 13-13.5% which shows a correlation of 99.63% with the computed porosity of the Rehmat-02 well. The observed low impedance and high porosity cube at the targeted horizon suggest that it could be a probable potential sand channel. Furthermore, the results of seismic post-stack inversion and geostatistical analysis indicate a very good agreement with each other. Hence, the seismic post-stack inversion technique can effectively be applied to estimate the reservoir properties for further prospective zones identification, volumetric estimation and future exploration.

**Keywords:** Probabilistic neural networks, model-based inversion, geo-statistical, effective porosity, impedance.

## Introduction

The application of seismic post-stack inversion is globally practised to delineate the reservoir properties. This technique mitigates the risk, uncertainty and cost of reservoir exploration for optimum resource exploitation (Yilmaz, 2001). Post-stack inversion transforms the seismic data into inverted impedance through the integration of seismic and well log data. Inverted impedance is further transformed into petrophysical properties i-e porosity, water saturation etc., using the PNN approach (Chen and Sidney, 1997). Production of hydrocarbon in a reservoir can be enhanced if the reservoir has sufficient permeability. The higher the permeability, the higher will be the effective porosity of the reservoir (Zhao *et al.*, 2013).

Model-based inversion technique is applied to estimate inverted impedance. There is an empirical relationship between inverted impedance and porosity. PNN approach is applied to transform impedance into porosity and to extract their non-linear trend. Porosity is estimated through both the methods; petrophysics and PNN technique. Moreover, estimated porosity is almost identical to well-based porosity which ranges from 13-14% with a correlation coefficient of about 99%. The resultant low impedance and high porosity zone demarcate a probable potential sand channel.

This study intends to estimate the reservoir properties through the integration of model-based inversion and geostatistical analysis for identification of hydrocarbon zone at the targeted depth of reservoir (B-sand of Lower Goru formation) in the area of Mubarak field, Lower Indus Basin, Pakistan.

## Materials and Methods

The seismic data provided by Directorate General Petroleum Concession (DGPC) consists of a 3D seismic cube and a Rehmat-02 well. The seismic data further comprises of navigation file and SEG-Y, whereas, the well data consists of various log curves among which sonic, density and neutron logs are used specifically for well-based porosity estimation. The seismic data in the time domain is interpreted using a synthetic seismogram and converted into a depth section using a single velocity function from a time-depth chart. Moreover, post-stack inversion transforms the seismic data into inverted impedance which is further converted into petrophysical properties e.g. porosity, using the geostatistical technique.

## Results and Discussion

To observe the regional distribution of structural geometry, seismic data is interpreted. Various faults are marked and horizons are picked with the help of a synthetic seismogram generated at Rehmat-02 well (Fig. 1).

Time grid is generated for B-sand reservoir which is multiplied with a single velocity function of 3011 m/s calculated from the time-depth chart. Therefore, a product of the time grid and velocity function gives the outcome of interpretation in the form of a depth contour map which shows that the depth varies from 3263 to 3310 meters. The contour map shows that the well is drilled on the shallower horst block of the structure (Fig. 2).
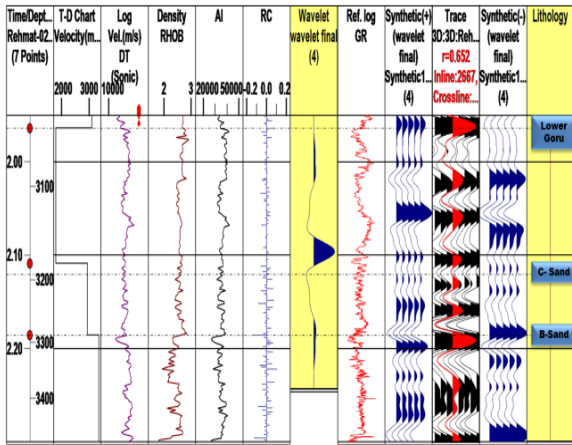
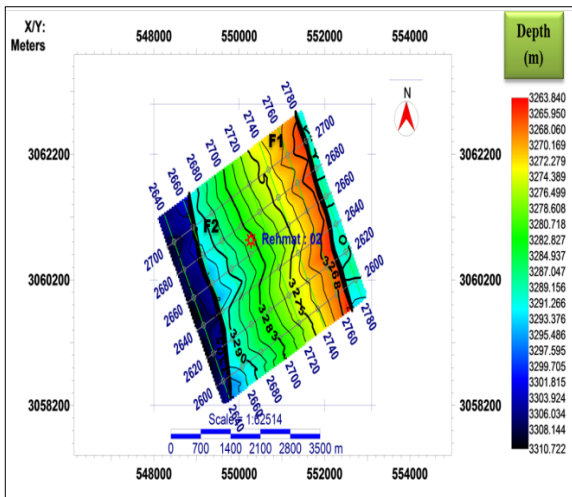Fig. 1 Synthetic seismogram of Rehmat-02 well.



Fig. 2 Depth contour map of B-sand reservoir.

## Petrophysics of B-sand Reservoir

For the quantification of the reservoir, petrophysical analysis is carried out at the depth of B-sand which ranges from 3283-3464 meters. The crossover formed by resistivity logs is marked which indicates the presence of hydrocarbon in the reservoir. The porous zone is best discriminated by the crossover of neutron-porosity and density-porosity log curves (Hester, 1999). The total porosity (PHIT) estimated in the zone of interest ranges from 16-17%, whereas the effective porosity (PHIE) ranges from 13-14% (Fig.3).
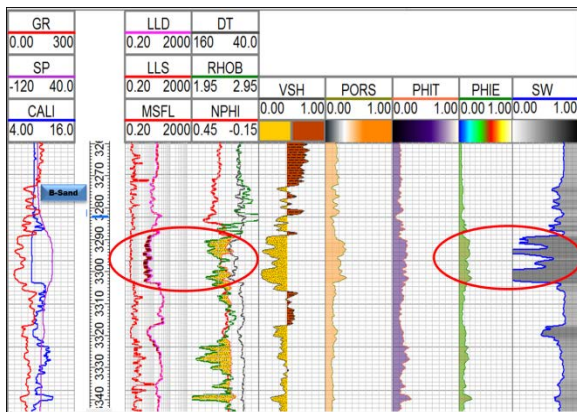


Fig. 3 Petrophysical analysis of B-sand reservoir.

## Post Stack Inversion

Seismic data gives information about the interface. However, inversion is applied to transform the interface property into layer property which can be correlated with well log data. Therefore, seismic inversion helps for improved characterization of reservoir formation (Ogagarue and Alaminiokuma, 2016; Nadin and Kusznir, 1995). The inversion technique comprises of wavelet extraction, initial/low-frequency model generation, inversion analysis and model-based inversion.

## Wavelet Extraction

Statistical wavelet is extracted from the seismic data within the time window ranges from 1800-2300 milliseconds with 200ms wavelength at the well location (Fig.4). The wavelet has a fundamental importance in seismic inversion. It is better to extract the wavelet from the actual data rather than using the theoretical wavelet (Cooke and Cant, 2010).
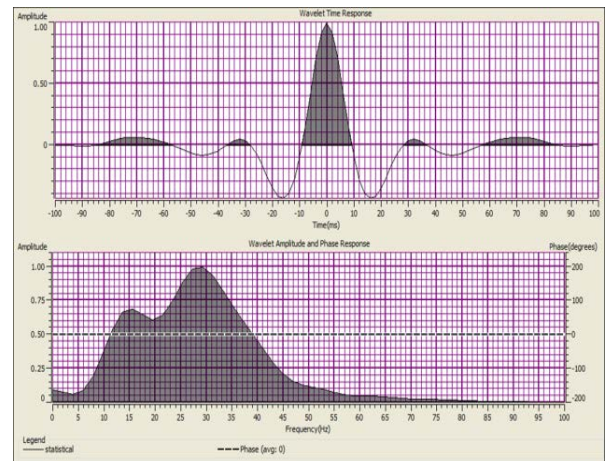


Fig. 4 Statistical wavelet for seismic post-stack inversion.

## Low-Frequency Model

An initial low-frequency geological model is generated within seismic time window ranges from 1800-2300 milliseconds using well log data (Fig.5). It provides frequency components omitted from the seismic data. Low frequencies act as a part of the algorithm in model-based inversion (Cooke and Schneider, 1983).

## Model-Based Inversion

Model-based inversion is based on the convolution theory. The convolution theory describes that normal incidence seismic trace can be modelled as the convolution of source wavelet with the earth's reflectivity series in addition to noise (Mallick, 1995) as shown in equation 1.

Seismic trace = (Wavelet * Reflectivity) + Noise      (1)

Model-based inversion starts with an initial low-frequency geological model and perturbs this model until an acceptable correlation between synthetic and actual seismic trace is obtained. It is an appealing

method because it cannot directly invert seismic data without acceptable correlation (Latimer *et al*., 2000).
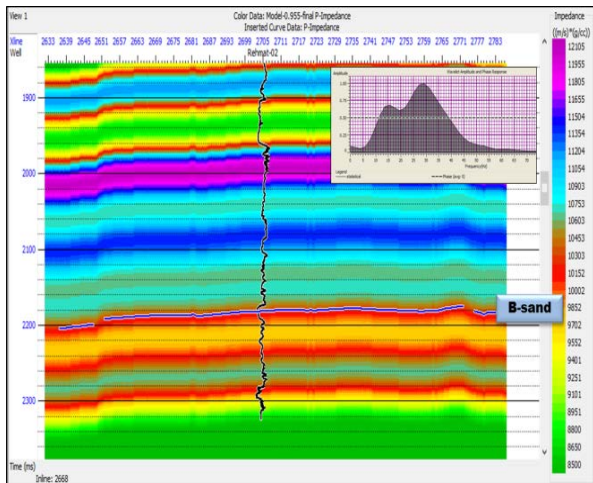


Fig. 5 Initial low-frequency model generated at well location.

The equation which transforms the reflectivity series into acoustic impedance is given as:

$$J = weight_1 \ x \ (S - W * R) + weight_2 \ x \ (M - H * R) \quad (2)$$

S is the seismic trace, W is wavelet extracted from seismic data, R is reflectivity series and the initial low-frequency model is denoted by M, H is the integration operator which is convolved with reflectivity series to produce the final impedance (Gavotti *et al*., 2013).

The first segment of the above equation models the seismic trace and the second segment models the initially estimated impedance. The generalized workflow for model-based inversion (Fig.6).
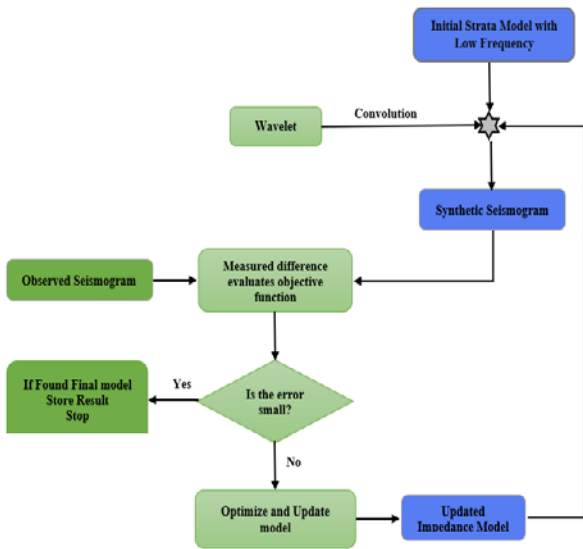


Fig. 6 Basic workflow adopted for model-based inversion (Sen, 2006).

**Results of Model-Based Inversion (MBI)**

The inversion analysis tool is a quality control check performed between model-based inverted impedance and well-based impedance (Mughal and Akhter, 2020). Model-based inversion has a correlation coefficient of 99.78%. The relative RMS (root mean square) error between inverted impedance and original impedance is

597.2 (m/s)*(g/cc) which suggests the efficiency and reliability of model-based inversion (Fig.7).
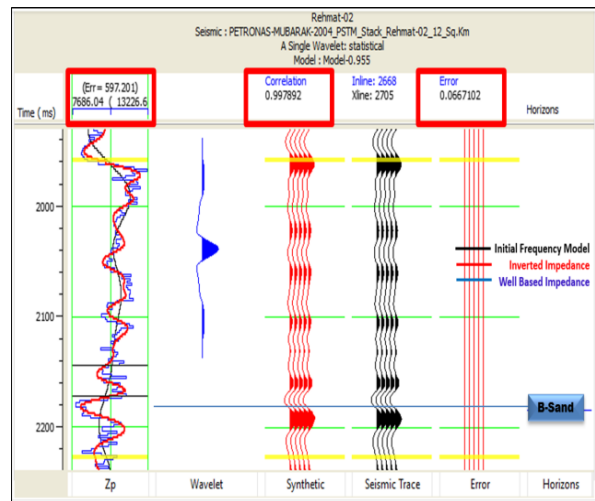


Fig. 7 Model-Based Inversion analysis window.

Figure 8 shows cross-section of inverted impedance with inserted p-impedance log curve across the reservoir. Section follows the trend of the initial geological model and has well captured the impedance of B-sand laterally as well as vertically because the wavelet is extracted within the time window of the reservoir. B-sand is picked at 2180 milliseconds having a low impedance ranges from 8400-8653 (m/s)*(g/cc) which is marked and indicated by the purple color.
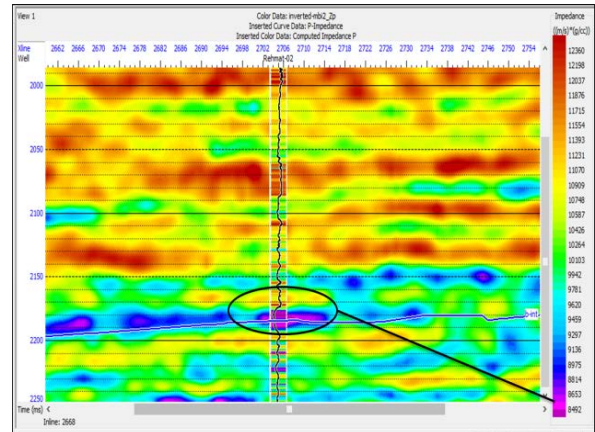


Fig. 8 Impedance section inverted by model-based inversion.

Inverted impedance estimated by MBI is populated over the whole seismic volume to observe the low impedance anomalous zone. Moreover, Impedance slice is extracted at B-sand depth which highlights the low impedance zone at the well location indicating the sand channel which is supposed to be responsible for the accumulation of hydrocarbon in that zone (Fig.9).

**Porosity Estimation**

An empirical relationship is established between p-impedance (x-axis) and effective porosity (y-axis) which is color coded by density (z-axis). A regression line is passed through the data points which shows an acceptable correlation of more than 80%. Moreover, a

zone is marked at the data points of low impedance and high porosity validated by low density within the reservoir formation (Fig.10).
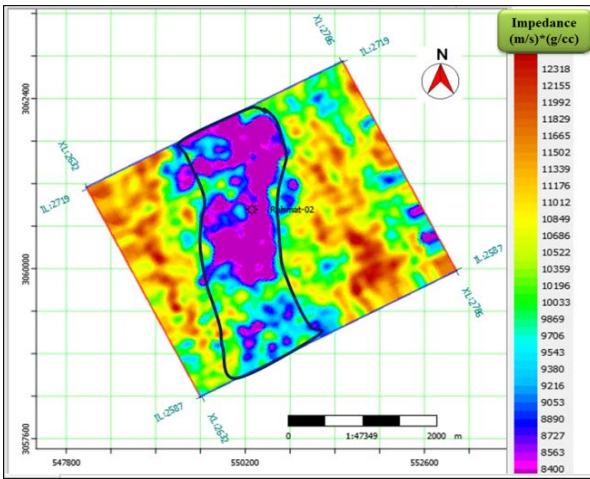


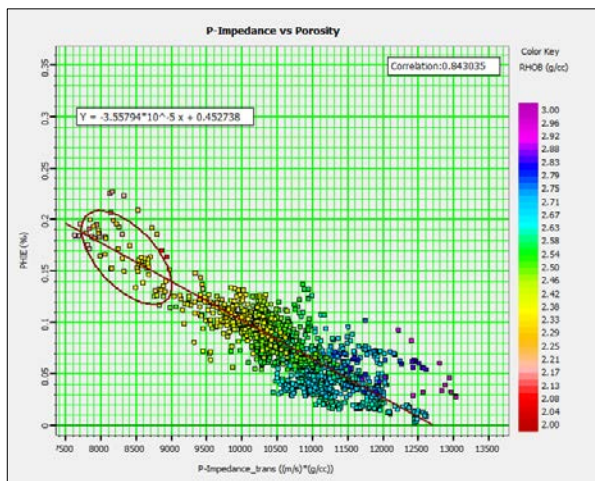Fig. 9 Inverted impedance slice extracted at B-sand reservoir.



Fig.10 Cross plot of effective porosity and P- impedance.

**Probabilistic Neural Networks (PNN) Analysis**

The probabilistic neural networks (PNN) is a geostatistical technique that is used to extract the non-linear relationship between different properties. It uses a weighted distance approach between the sample points for the interpolation of data points (Mahmood *et al.*, 2017). Porosity is estimated using a probabilistic neural networks taking inverted impedance as an external attribute which is trained by the well log porosity curve until maximum numbers of iterations are completed.

**Porosity Comparison**

The result from MBI is used as an external attribute for porosity estimation. Estimated porosity shows an excellent correlation of 99.6% with well based actual porosity curve in cross plot and best matches in their training result. Modelled effective porosity is about 13.71% which is close to the actual porosity of 14%. Therefore, the actual porosity and estimated porosity are cross plotted (Fig.11).
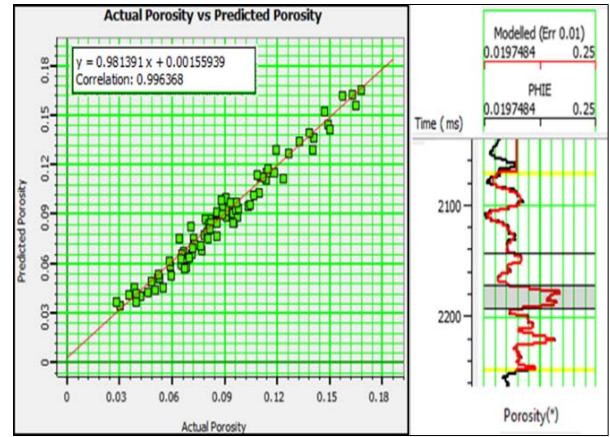


Fig. 11 Cross plot of actual porosity and modelled porosity with their training result.

Inverted porosity estimated by PNN is populated over the whole seismic volume to observe the porous zone away from the well control. Moreover, porosity slice is extracted at B-sand which validates that the well is drilled over the sand body of high porosity and low impedance (Fig.12).
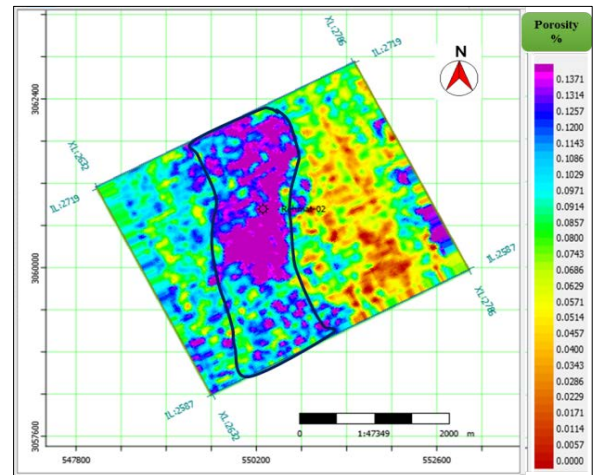


Fig.12 Inverted Porosity slice extracted at B-sand reservoir.

**Conclusion**

The research work intended to estimate the effective porosity which is very crucial for hydrocarbon production and reducing the uncertainty of sand reservoirs far beyond the well control.

3D seismic data is inverted into acoustic impedance utilizing a model-based inversion algorithm. It resolved the low impedance zone in the time window domain of 2175–2185 milliseconds. PNN transforms the impedance into porosity and extracts their non-linear relationship. The estimated porosity ranges from 13-13.71% and has a correlation coefficient of about 99% with the observed porosity. Moreover, extracted porosity slice shows its higher values along the observed sand channel which is consistent with the lower values of the inverted impedance slice.

Therefore, it can be observed that the results of petrophysical analysis, seismic inversion and PNN

techniques are in very good coorelation with one another.

Hence, the integration of these robust and vigorous techniques are useful for further prospect development and enhancing production in the evaluated zone of B-sand interval of Lower Goru reservoir and other reservoirs present in different regions under similar geological settings.

## Acknowledgement

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