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Probabilistic neural network approach for porosity prediction in Balkassar area: a case study

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Abstract

This study is intended to build a stratigraphic architecture through demarcation of potentially prospective zones through porosity prediction using the Artificial Neural Network. Artificial Neural Network has gained a considerable amount of attention over the past few years among different linear and nonlinear prediction tools such as curve fitting. The current study predicts the reservoir porosity using 3D seismic data and well logs of the Balkassar Oil field. Therefore, to obtain acoustic impedance volume, the 3D seismic data is inverted and applied to the data set by using as a part of seismic attribute study. The stepwise regression and validation testing is found to provide the best results for seven attributes which are used for training the Neural Network, which showed a substantial amount of correlation. On this basis, porosity volumes are predicted. These volumes are used to define zones that could describe the distribution of porosity in the Balkassar Oil field and could be helpful in determining prospective zones. Otherwise it would not be promising by 3D seismic amplitude data. In this way, contemporary research has important implications for future exploration.

Keywords: Artificial Neural Network; Petrophysical analysis; Porosity prediction; seismic attributes, Prospective zones.

1. Introduction

In the reservoir characterization of carbonates, the major problem encountered is the delineation of fractured carbonates, which play an important role in defining the boundaries of fractured and porous carbonates (Kazmi and Jan, 1997). This kind of problem can be solved using the modern techniques like the generation of attributes derived from seismic data, which could be connected physically to the reservoir properties(Khan et al.,1986). This relation between the reservoir properties and attributes derived from the seismic data is helpful in predicting the reservoir properties in the inter-well region (Hampson et al., 2001). This technique can be applied with the help of neural network analysis or multilinear regression approach.

These results can be achieved using multilinear regression approach or neural network analysis. After computation, these properties are then interpolated to the whole seismic volume with the help of impedance and seismic attributes. After the establishment of relationship between petrophysical properties and attributes derived from seismic, the reservoir properties like fluid content, lithology and productive zones boundaries could be predicted (Curia, 2009).

In this research work, the adopted methodology is based upon the combination of seismic attributes, acoustic impedance, processed logs and artificial neural network training (Basu and Verma, 2013). The reservoir property predicted in this study is porosity, on the basis of which the lateral extent of the carbonate reservoirs is marked and existing reservoir model is further refined.

2. Methodology adopted

The methodology which is adopted to predict the reservoir properties includes the estimation of a nonlinear operator. This nonlinear operator is then used to predict the well logs from the adjacent seismic attributes data (Lindseth, 1979). With the help of these predicted logs, the mapping of attribute volume of porosity along with cross-sections is carried out (Bender and Raza, 1995). For this purpose, a 3D seismic volume of Balkassar area, and secondly to tie the seismic data, a series of wells that is Balkassar OXY-1 and Balkassar OXY-2, are used.Both the wells are holding the target log of porosity, which needs to be predicted for other locations. The check shot corrected sonic logs are incorporated in Balkassar OXY-1 and OXY-2 wells for converting the data from depth domain to time domain. Thirdly, the 3D seismic volumes in the form of "external" attributes are also included in the data. If the external attributes are absent, then the analysis is restricted to the internal attributes which can be calculated from the raw seismic data.

2.1 External Attributes

The attribute is considered to be an external attribute, if it cannot be calculated within the environment of seismic trace data, which includes AVO attributes, impedance etc. (Demin, 2003). The calculation of this attribute involves the data from other sources other than seismic trace data (Basu and Araktingi, 2009). Seismic trace inversion is one of the example.

2.2. Internal Attributes

The internal attributes are those attributes, which are generated by applying mathematical transforms upon the seismic amplitude or trace data (Dorrington and Link, 2004). Examples are trace envelope, instantaneous phase, amplitude weighted cosine phase etc.

2.3. Target Log Determination Using Attributes

Non-linear relation is required between the attributes for the analysis. To achieve goal various other attributes, which show a non-linear behavior,are used instead of using the raw seismic data. It is helpful in increasing the predictive power of the technique (Bourgoyne et al., 1991), because the non-linearity achieves this by breaking the input data into the component parts. This whole process is named as feature extraction or pre-processing, which can firstly improve the ability of recognizing the pattern to a great extent, and secondly it reduces the dimensionality of the data, before being used to train the system. The previous knowledge could also be addedto the design of the pattern recognition by adopting this pre-processing.

$$\begin{bmatrix} \varphi_1 \\ X_1 \\ Y_1 \\ Z_1 \end{bmatrix} \begin{bmatrix} \varphi_2 \\ X_2 \\ Y_2 \\ Z_2 \end{bmatrix} \begin{bmatrix} \varphi_3 \\ X_3 \\ Y_3 \\ Z_3 \end{bmatrix}$$

Log Values

Attributes

… Equation A

2.3.1. Mathematical Illustration

The neural network proves helpful in offering the non-linear solution to the problem, as it can enhance the resolution of derived attribute volumes and the predictive powers as well. In this research work, the probabilistic neural network approach is applied to the data, which is analogous to kriging interpolation technique (Specht, 1990). If we assume that the exact value of the desired attribute of porosity is known, then the main aim is to calculate the new output point

$$\begin{bmatrix} ? \\ X_0 \\ Y_0 \\ Z_0 \end{bmatrix}$$

……………… Equation B

This problem can be overcome by comparing the new with the known attributes. The predicted value is a linear combination of the known training values, in a probabilistic neural network approach.

$$\varphi_0 = \omega_1 * \varphi_1 + \omega_2 * \varphi_2 + \omega_3 * \varphi_3 \quad \textbf{… Equation C}$$

In the above equation, porosity is abbreviated as φ, * is showing the convolution, while ωi are representing the weights. These weights basically rely upon the distance between the desired point to the training point.

3. Prediction Workflow

3.1. Petrophysical Evaluation

For the formation evaluation purpose, the petrophysical analysis of Balkassar Oxy-1 and Oxy-2 wells is performed, which is used for the prediction of reservoir properties. Using various well logs like Neutron, Density, Gamma Ray etc. the reservoir porosity for the respective wells is calculated (Shahraeeni and Curtis, 2011). With the help of this computed property, also known as "target logs" the artificial neural networks are trained for the prediction of porosity. This analysis is applied over the Eocene aged Chorgali and Sakesar formations and Paleocene aged Patala and Lockhart formations. The computed petrophysical analysis results are shown in figures 1 and 2 for Balkassar Oxy-01 and Oxy-02 respectively.

3.2. BalkassarWells Correlation Results

The formation markers with their corresponding depths and Gamma ray logs are used to perform the correlation of Balkassar wells in order to identify the continuity and lateral extents of the formations of interest (Gardner et al., 1974). The well correlation results of Balkassar Oxy-01 and Oxy-02 are shown in figure 3. To aid the prospective zone delineation and reservoir property prediction, the well correlation results are used to define the lateral extent and continuity of prospective zones.

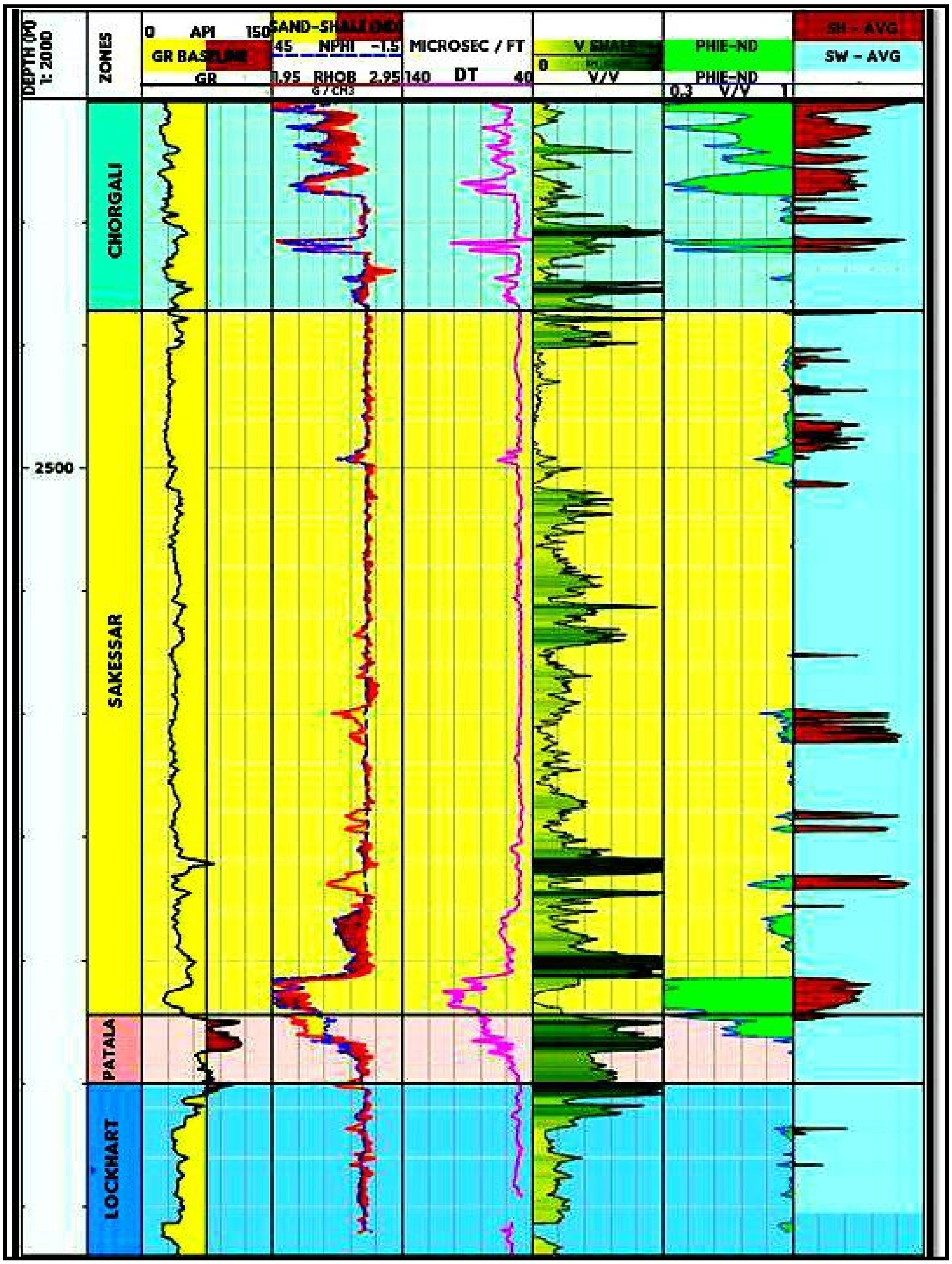

Fig.1. Petrophysicalevaluation results of Balkassar Oxy-01 well.

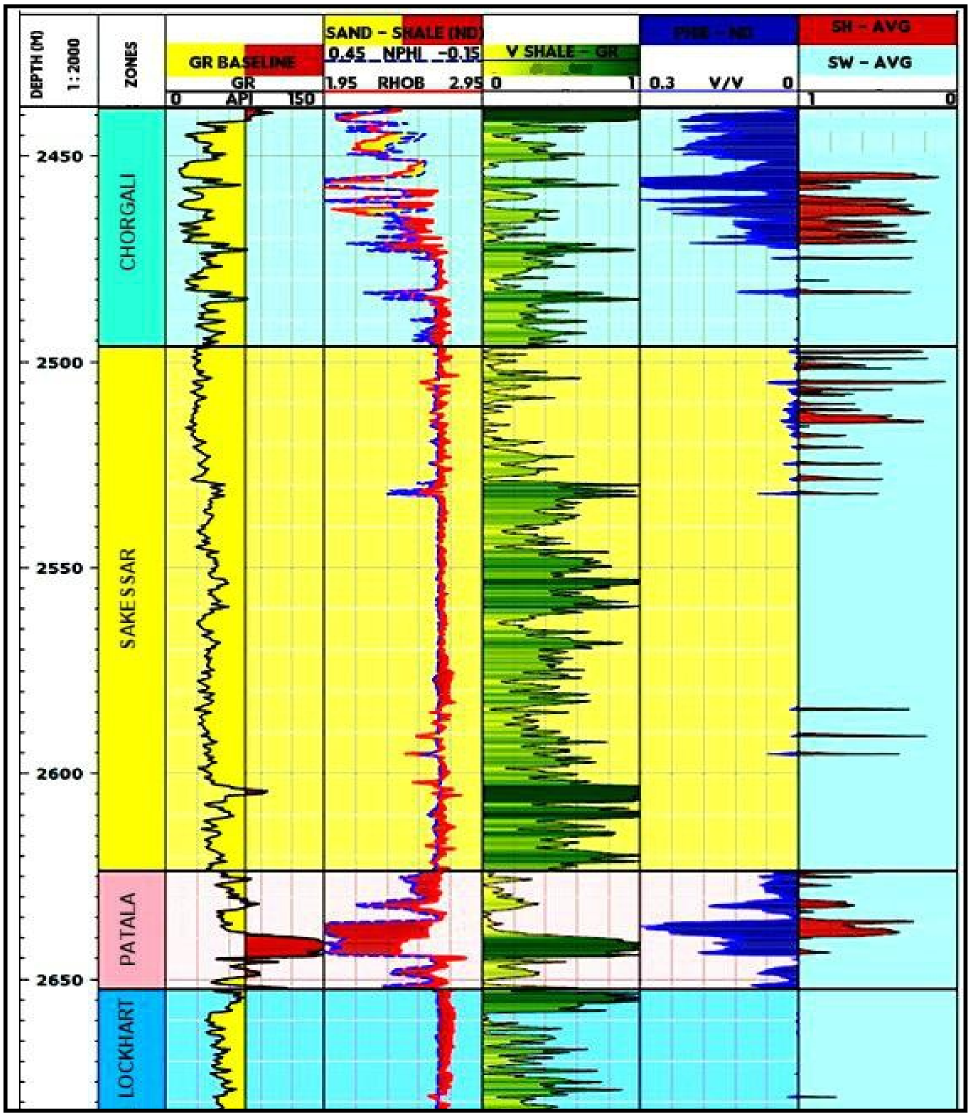

Fig. 2.Petrophysicalevaluation results of Balkassar Oxy-02 well..

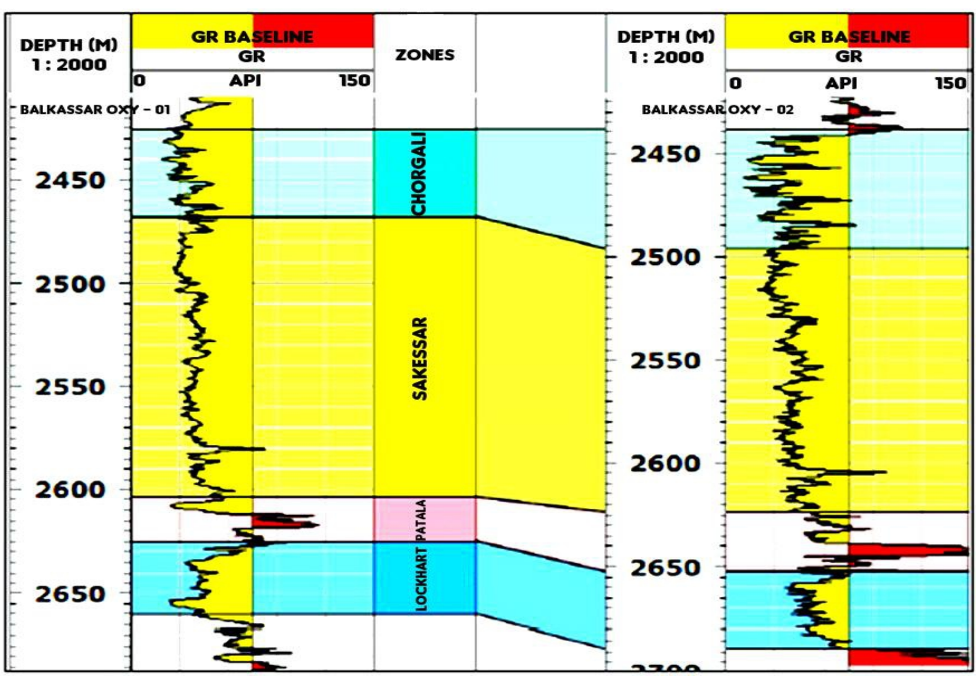

Fig. 3. Well correlation between Balkassar Oxy-01 and Balkassar Oxy-02 wells.

3.3. Artificial Neural Network Results for Porosity Prediction

In order to perform the multi attribute analysis, the neural network based inversionis used to generate the impedance volume (Sen, 2006). The porosity logs are predicted at well locations using the Artificial Neural Network (ANN), then through Probabilistic Neural Network (PNN) these porosity logs are extrapolated over the whole impedance volume (Liu and Liu, 1998). The training results of neural network are shown in figure 4. The external attribute in this case is the impedance volume, while the internal attributes include the horizon information and the seismic data (Malleswar et al., 2010).

The training results of neural network for porosity prediction are shown in application plot in figure 5. The trained network cross-correlation is 0.991619 with the average error of 0.0121 (fraction). Figure 6 shows the cross plot between the actual and predicted porosity. The trained probabilistic neural network is then validated, and after validation the resulting correlation comes out to be 0.770736 with an average error of 0.0576275 (fraction). The final validated result is applied to the impedance cube for porosity prediction and porosity cube is generated. The computed porosity log is overlaid on the respective lines of Balkassar Oxy-01 and Oxy-02 wells from the porosity cube, as shown in figures 7 and 8.

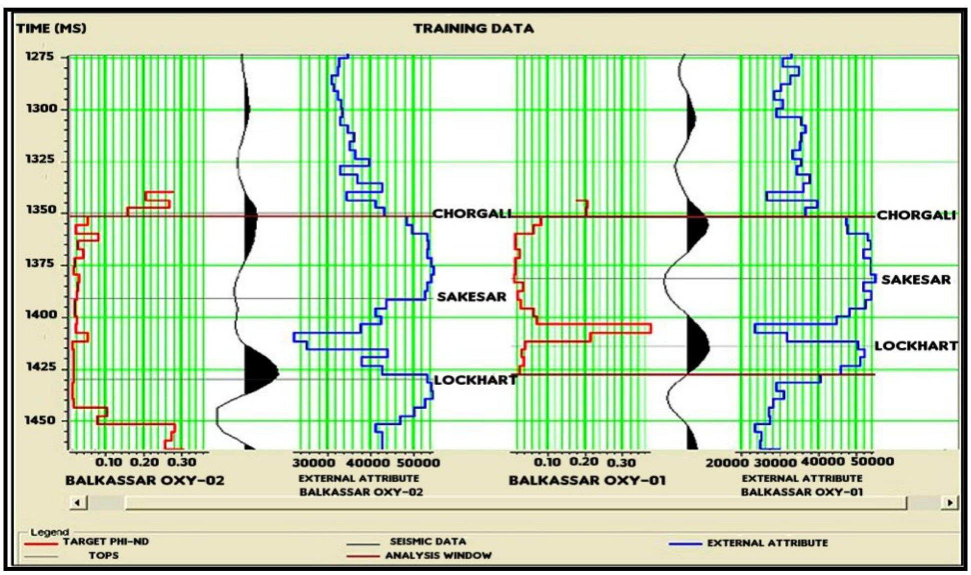

Fig. 4.Training of probabilistic neural network results for porosity prediction using Balkassar Oxy-01 and Balkassar Oxy-02 wells.

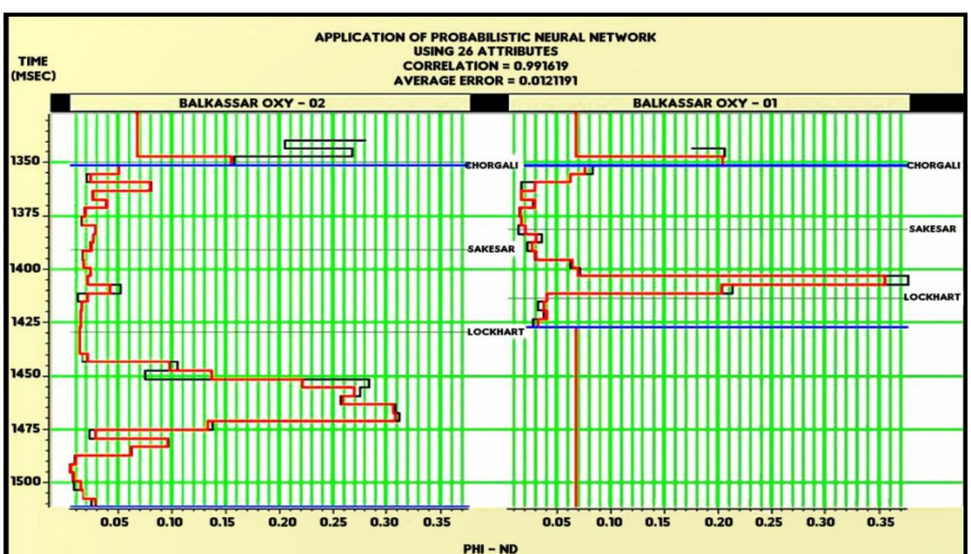

Fig. 5.Training results of Probabilistic Neural Network for porosity prediction.

The porosity predicted through probabilistic neural network shows a fair amount of correlation with the porosities estimated from well logs (Russell, 2013), as shown in figures 7 and 8. From the porosity volumes computed for Chorgali, Sakesar and Lockhart formations, the horizons maps with average 10 msec window above the event are generated. In order to define the structural boundary on the horizon map, a frontal thrust F1 with two back thrusts F2 and F3 are marked.The prospective zones on the average porosity maps have been highlighted for the concerned horizons by a black circle as shown in the figures 9, 10 and 11 respectively. The high porosity zones are fault bounded on which Balkassar Oxy-01 and Oxy-02 wells have already been drilled, thus validating the presence of high porous zones. The younger back thrust F3 has fabricated the Balkassar anticline in to eastern and western compartments. The eastern compartment is proved to be more prospective having high porosity values at Sakesar and Lockhart level while effect of compartmentalization is absent at the level of Chorgali Formation.

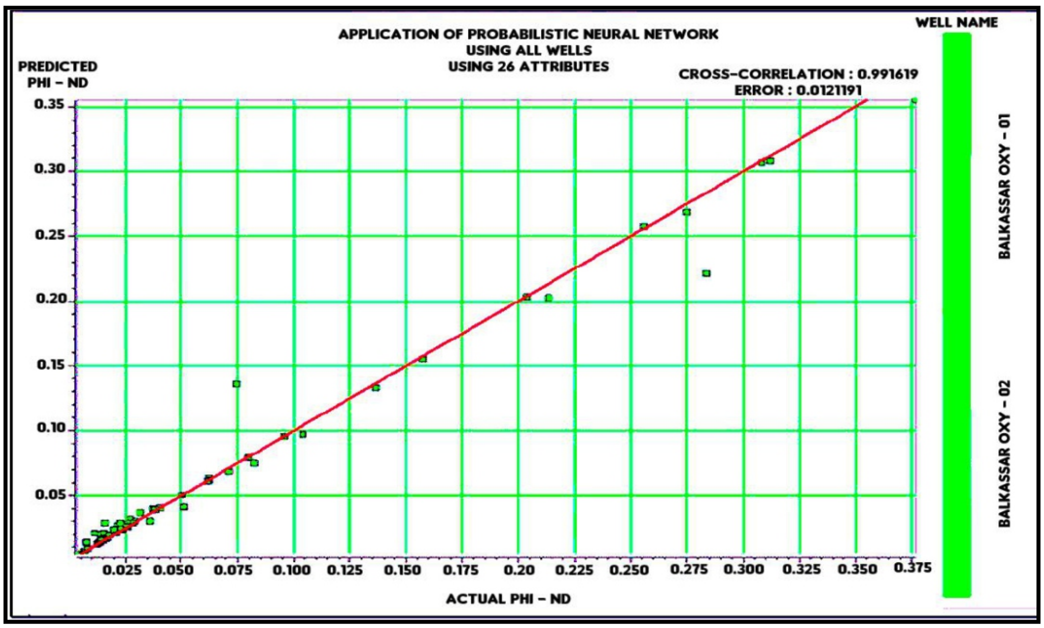

Fig. 6.Cross plot between the actual porosity at well location and predicted porosity.

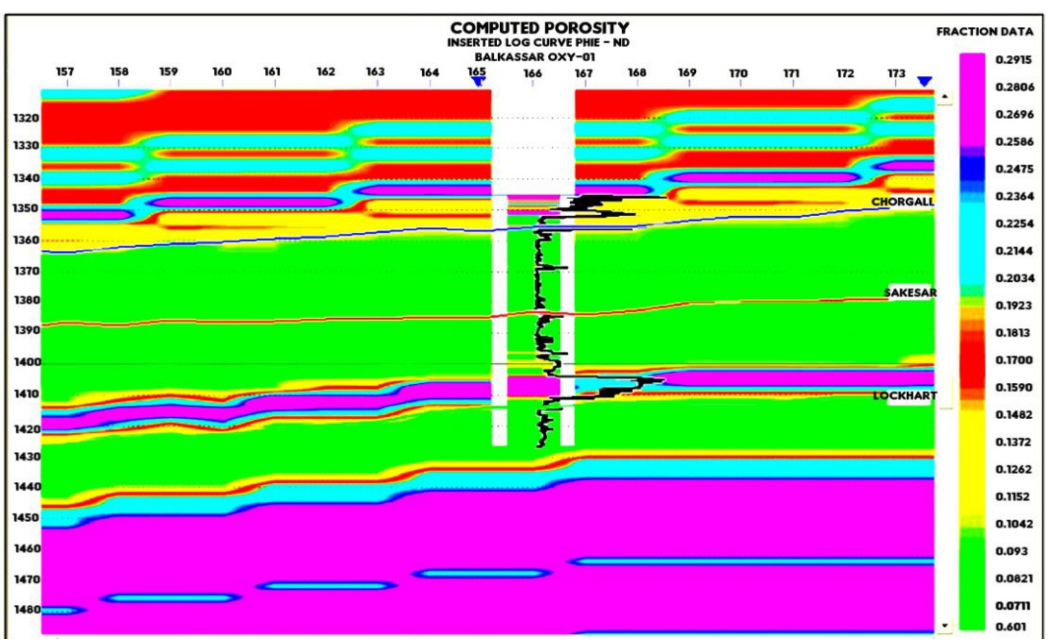

Fig. 7.Inserted well-based porosity log on Inline 235 from porosity volume, estimated at well Balkassar Oxy-01.

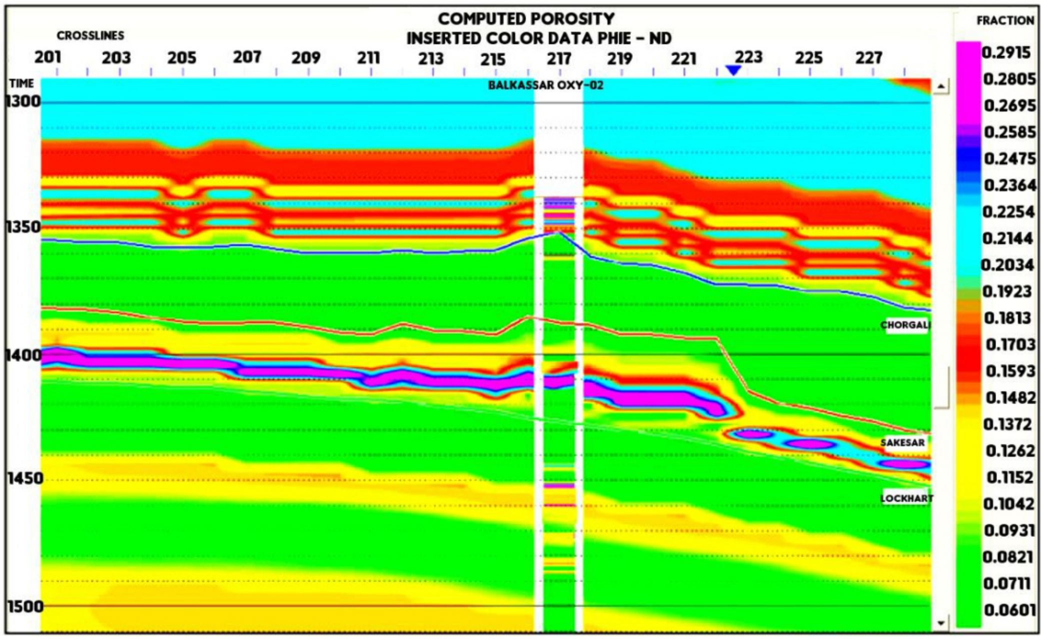

Fig. 8.Inserted well-based porosity log on Inline 149 from predicted porosity volume, estimated at wellBalkassar Oxy-02.

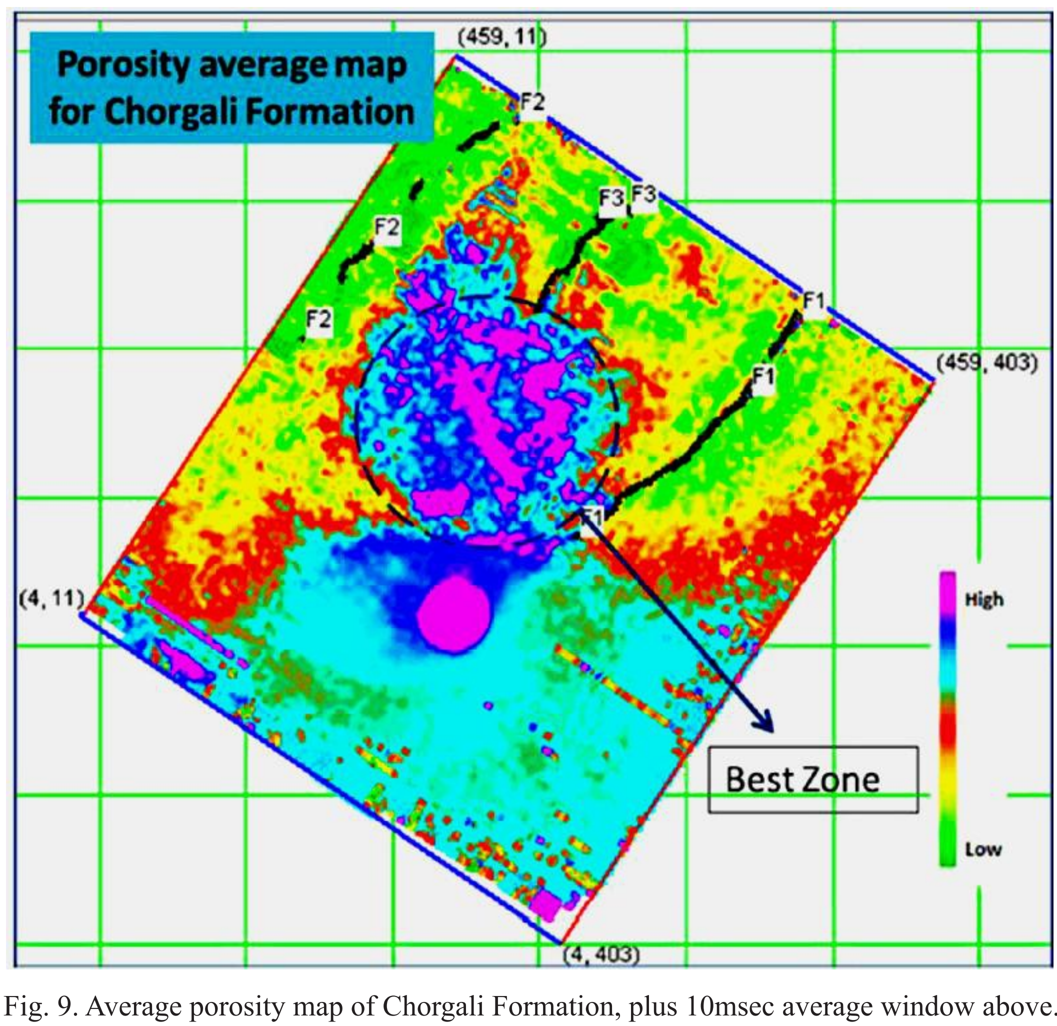

Fig. 9. Average porosity map of Chorgali Formation, plus 10msec average window above.

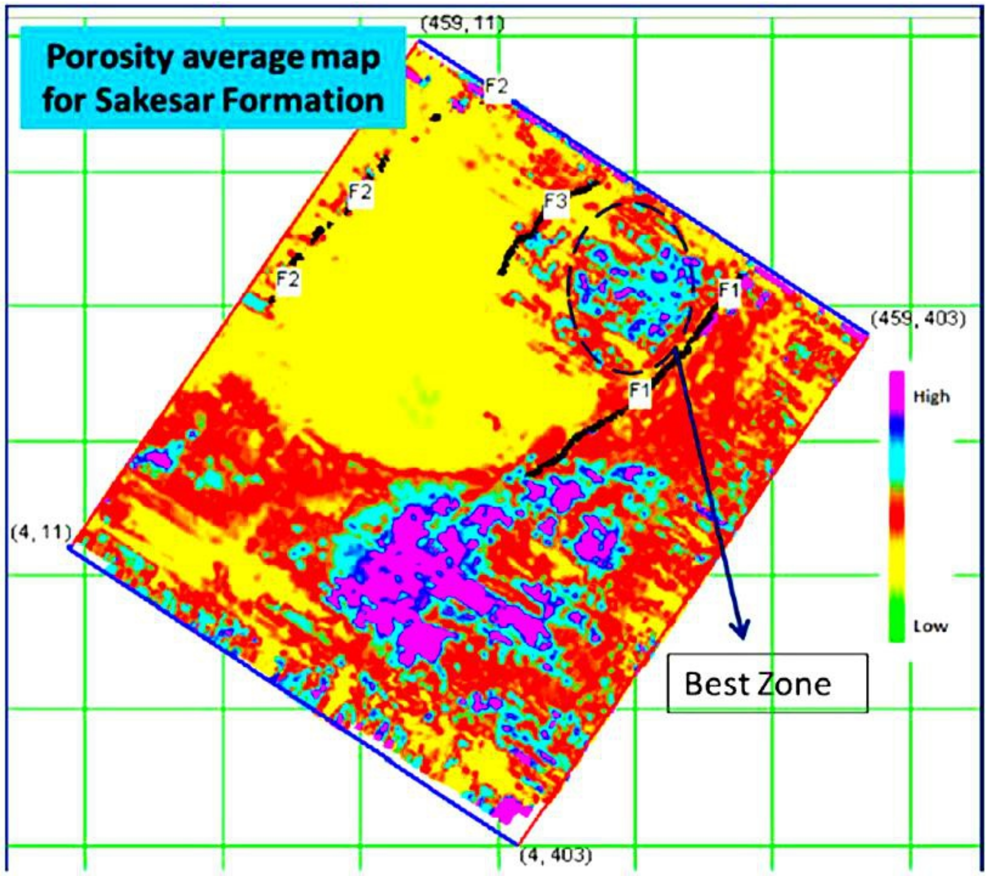

Fig. 10. Average porosity map of Sakesar Formation, plus 10msec average window above.

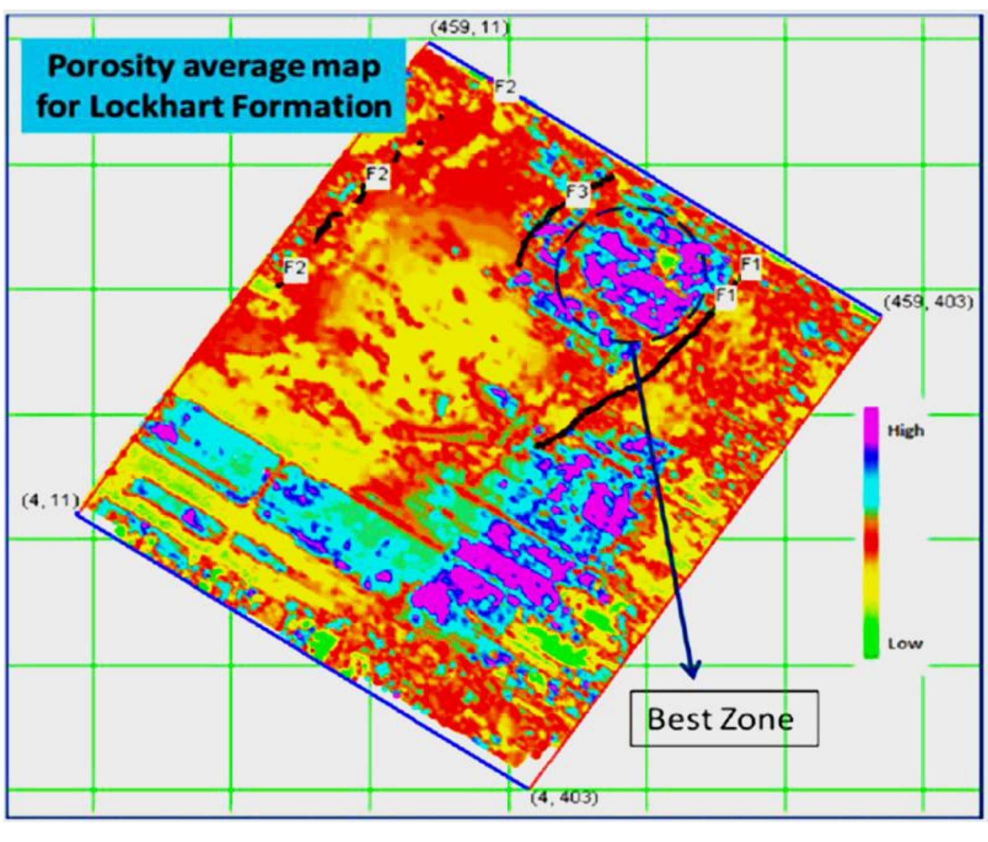

Fig. 11.Average porosity map of Lockhart Formation, plus 10msec average window above.

4. Discussion

Porosity is a fundamental characteristic of a reservoir system that is typically distributed in Balkassar structure in a spatially non-uniform and non-linear manner. In this study, the artificial Neural Network Approach proved to be fruitful for porosity prediction by using the well log data of Balkassar Oxy-01 and Oxy-02 wells. The high degree of correlation between actual and artificial neural network predicted porosity helped in reservoir characterization of Balkassar anticline at Eocene and Paleocene levels. Using the probabilistic neural network, these porosities are extrapolated onto the whole impedance volume. After validation the porosity cube is generated, which showed a very good correlation results between porosity predicted through probabilistic neural networks and porosity estimated from well log data. The horizon maps are generated for Chorgali, Sakesar and Lockhart formations and interpreted for high values of porosity.

5. Conclusions

This research work is based upon the prediction of reservoir properties in the inter-well regions using the technique of artificial neural networks. This whole research proved helpful in the identification of prospective zones on the 3D seismic volume. The background impedance model is constructed to recover the low frequencies of seismic data which are lost due to the processing and acquisition artifacts. This background impedance model is constructed after establishing the seismic to well tie using seismic amplitude data and horizon information. Using the background impedance model, the neural network analysis shows a cross-correlation of 0.914464 with an average error of 3300.2 [(ft/s)*(g/cc)]. After the validation step, the cross-correlation between the impedance computed on seismic amplitude data and impedance logs estimated at the well locations, come out to be 0.894665 with an average error of 3644.03 [(ft/s)*(g/cc)]. The predicted porosity correlation is 0.991612 with an error of 0.121191 and after the validation step is carried out the correlation come out to be 0.770736 with an error of 0.0576725. These computed results are applied to train probabilistic neural networks to predict the porosity volume.Afterwards, average porosity maps are constructed to define the lateral variations of porosity values and the prospective zones with low risk of well failure in sense of hydrocarbon production are identified.

Authors' Contribution

Muhammad Fahad Mehmood is the main author and this research is part of his PhD research. Urooj Shakir was involved in data interpretation. Muhammad khubaib prepared maps and figures. Mumtaz Ali Khan did the formatting and technical changes. Nimat Ullah Khattak critical reviewed the article. Hafiz Shahid Hussain critically reviewed the article and formatted the manuscript. Abdur Rehman reviewed the article.

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