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Multi attribute transform and Probabilistic neural network in effective porosity estimation-A case study from Nardipur Low area, Cambay Basin, India

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Summary

This study focuses on one of the oil fields located east of Kalol main field in Nardipur Low area of Cambay Basin. The major reservoir unit in the interested area consists of mainly alternating coal, silt, shale and occasionally fine to medium grained sands as channel fills, crevasse splay deposited in lower delta plain environment. In the available 3D seismic data, the coal layer occurring at the top part of Kalol-IX litho unit and the pay sand capped by thin shale layer below the coal layer are not resolved and generate a composite detectable seismic response, making reservoir characterization difficult through conventional seismic attribute analysis.

The main aim of this study is to generate effective porosity volume for detailed reservoir characterization of the area. The effective porosity distribution using Multi attribute transform approach is found to be most effective in prediction of porous pods in the area.

The 3D seismic volume was inverted to obtain an acoustic impedance (AI) cube through model based inversion. This inversion helps in improving the vertical resolution which might enhance the perceptibility of thin reservoir layers. The model based inversion has been selected as the main seismic attribute. Subsequently, acoustic impedance attribute along with other attributes from seismic volume were analyzed using multi attribute regression and Probabilistic neural networks (PNNs). To estimate the reliability of the derived multi attribute transforms, cross validation is used. According to the results, it is found that the cross correlation between actual effective porosity derived from well logs and estimated one is around 72% using multiple regression transform while the same increased to 98% when PNN is used. Finally, based on cross validation result, PNN is used for effective porosity prediction.

Porosity slices generated from the predicted volume is found to be validated at well location. This has enhanced the confidence level in field development.

Keywords: *Multi-attribute transform, Neural Network, Cambay Basin*

Introduction

While doing reservoir studies in clastic environments, the two major issues addressed are, finding productive sands and defining the boundaries of these sands. The modern approach towards solving these type of problems involves generating seismic attributes that are physically related to the reservoir properties and combining these attributes to predict the petrophysical properties of the reservoir (Hampson et al., 2001). This process can be accomplished using either multilinear regression or neural network analysis. Once the relationship between the attributes and the petrophysical parameters are established, then these

properties can be populated in the whole volume using the seismic attributes and impedance. This, in turn, helps in inferring the lithology, fluid content, and boundaries of the productive zones.

The methodology involved in this process is based on the combination of processed log, acoustic impedance and seismic attributes, and neural network training. In this study, porosity volume is predicted, which is then used to describe the spatial extension of the sand facies of interest and validation and refinement of the existing porosity model.

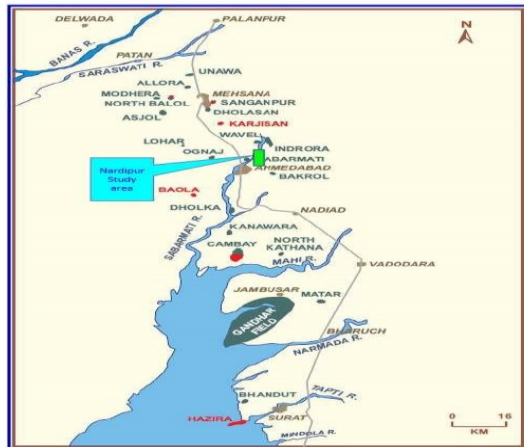


Fig1: Location map and area of study in Cambay Basin

Location and Geological Setting

Cambay basin situated on India's western continental margin, is an intra-cratonic graben flanked on the North-East by the Aravalli orogenic belt, on the East and South-East by Deccan craton and on the West by Kathiawar uplift. The general trend of the basin is NW-SE. Some of the major transverse trends of the basin are reactivated, giving rise to different discrete tectonic elements from North to South of the basin. These transverse faults are parallel to the Aravalli trend in the North and to the Satpura trend in the South. The Nardipur Low considered to be the depocentre for generation of hydrocarbons and is flanked by a number of fields such as Limbodra, Mansa and Indrora in the East and Kalol, WaduPaliyad, Nandasan, Sobhasan in the West (Fig. 1).

However, in Nardipur low, hydrocarbon potential of K-IX pay is also well established through drilled wells. The main pay Kalol Formation in this part of the area was deposited in deltaic complex, traversed by distributary channel networks, occasionally having tidal influence. The lithology of K-IX to K-X Unit of Kalol Formation consists of mainly alternating coal, silt, shale and occasionally fine to medium grained sands as channel fills, bay fills and crevasse splays deposited in *lower delta plain environment*. The delta plain was a deposits, inter-distributary bay, and crevasse splay-natural levee and marsh deposits. Although, lower delta plain was dominated by fluvial processes, distributary channels were influenced by marine processes such as tidal fluctuations. Since the sand distribution was through distributaries and winnowing action by tidal influence, the sand dispersal pattern has a complex geometry spatially. Also, there was

little migration of distributary channels in this part of delta. The active channel course was having good sand developments in its axial part. These channels are having limited width ~ 200300 m. The abandoned channels are having marshy and swampy environment marked by coal, carbonaceous-shale, while the overbanks have shale and silty-shale. Frequent alternations of sand-shalecoal sequences indicate slow progradation and rhythmic deposition during Kalol Formation. The sands encountered in Kalol Formation are thin and discrete in nature, commonly representing channel fills, and crevasse splays etc. The drilling of wells has proved complex nature of the K-IX pay in the area which is a common feature of lower delta plain environments. The wells of Limbodra field lying in the Nardipur low/syncline have invariably produced oil from subtle traps within Kalol IX pay. The exploration and development thrust is given to locate hydrocarbon traps in the syncline and in its rising flank/trend. The generalized stratigraphy of the area is provided in (Fig.2).

Data Description

Seismic data:

The data is of 36 fold with sampling interval 2ms and record length of 5sec. Quality of seismic data is fair to good having dominant frequency of 30Hz and band width of 10-70Hz in the zone of interest.

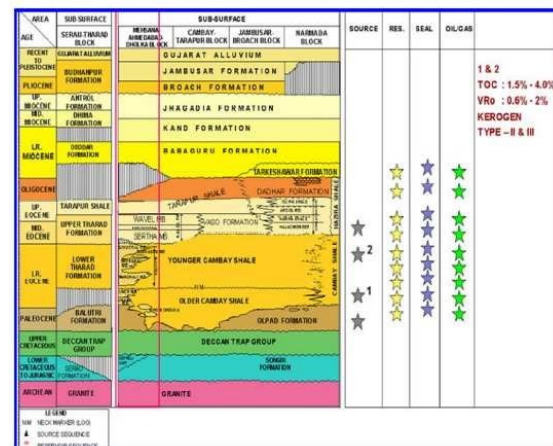


Fig2: Generalized Stratigraphy of Cambay Basin. Main target-Sertha member in Nardipur low with stratigraphic entrapment mainly concentrated on the flank of the low.

Well data:

The present study was confined to Kalol section and in particular K-IX pay sand. Total nineteen wells were used

in this study. Conventional logs (GR, SP, RT, RHOB, NPHI, DT) were available for all the wells. Synthetic seismogram was prepared for tying seismic with well data in the study area.

Present Study

Log processing:

All the wells used for the study were processed with after conditioning and applying suitable environment correction. The target zone of processing was within Kalol Formation and in particularly K-IX unit. Two interpretation models, sand-shale and coal-shale with Quartz as the main matrix mineral along with Kaolinite and Chlorite as the clay minerals and muscovite in traces, has been used. Standard petrophysical parameters were used for processing i.e, $a=0.62$, $m=2.15$ and $n=2$ and $Rw=0.24\Omega m$ at $81.5^{\circ}C$. The effective porosity (PIGN) was determined using RHOB, NPHI and DT log data. Fig.3 shows the processed output. Effective porosity determined from the logs was taken as target for training/prediction from seismic attributes by Multi Attributes Transform analysis and PNNs.

Log correlations:

Lithologies encountered in the drilled wells show that the coal, shale and silt layers, which are present in the Kalol Formation, generate a noticeable discrete response on the electro-logs. High resistivity, low GR, low RHOB, high NPHI and high DT depicts coal units (Fig.4). The K-IX sands depict relatively high resistivity and low GR when compared with overlying and underlying shales and depict crossover in the RHOB and NPHI logs where hydrocarbon are present. Most of the sands show coarsening upward sequence.

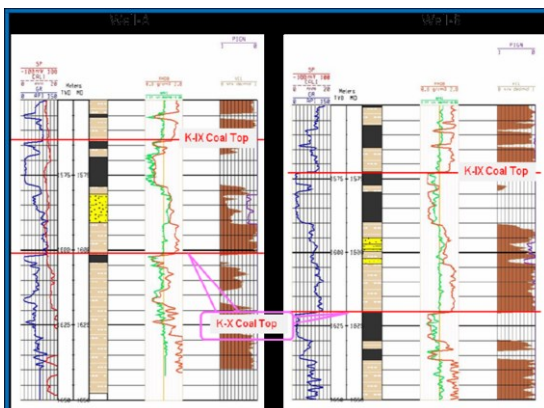


Fig3: Para-Log of two drilled wells in the area.

Electro-log correlation profiles were prepared in dip, strike and NE-SW direction to bring out spatial facies distribution and temporal lithological variations in Kalol-IX formation. Analysis of these log profile suggest that the major depositional sequence consist of *bay-fill deposits and abandoned distributary channelfill deposits*.

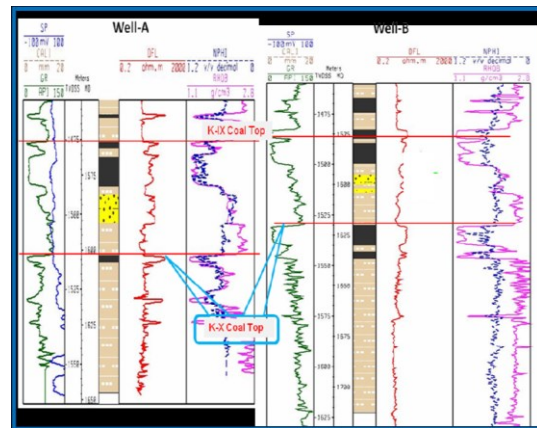


Fig4: Representative Log motif of K-IX Pay zone.

Based on log motif (Fig.4), the K-IX lithounit may be divided into three subunits. The lower part is mainly shale with occasionally silt and very fine sandstone, the middle unit consists of fine grained sandstone and siltstone which is the main pay zone in the study area capped by a shale layer and finally the coal at the top, which is the upper unit of K-IX lithounit. At some places the middle and lower lithounit shows the presence of coal and/or carbonaceous shale suggesting multiple coarsening upward sequences followed by fining upward sequence and finally overlain by deposition of coal.

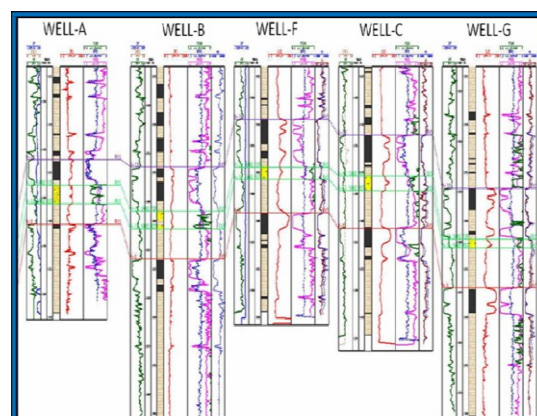


Fig5: Electro log correlation in NE-SW direction.

Seismic data Analysis:

The main aim of this study is to generate effective porosity volume for detailed reservoir characterization of the area along with the depositional model in light of positive results of two newly drilled wells Well-A and Well-B. Total 13 wells of Limbodra field along with 6 wells of Kalol field which fall in the Nardipur Low area were used for porosity prediction. The synthetic seismograms for all the wells with DT log were prepared for seismic to well tie. Synthetic seismogram of recently drilled wells, Well-A and Well-B is shown in the (Fig.6). The correlation factor is around 80-85%.

Correlation of major surfaces is shown in arbitrary line passing through different wells (Fig.7). Basic interpretation has been carried out using Landmark Application software for making Time structure map and Isochronopach. Seismic inversion and porosity prediction analysis were carried out using STRATA and EMERGE module of Hampson Russell software (HRS).

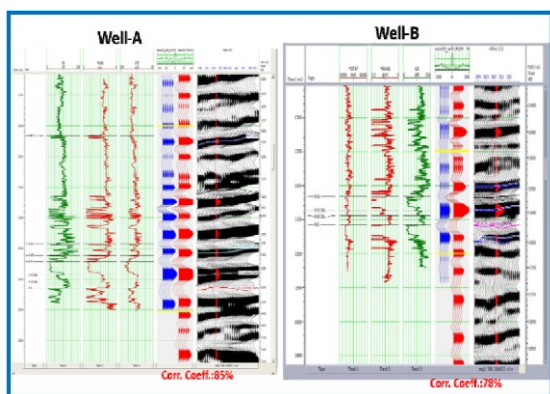


Fig 6: Synthetic seismogram of Well-A and Well-B.

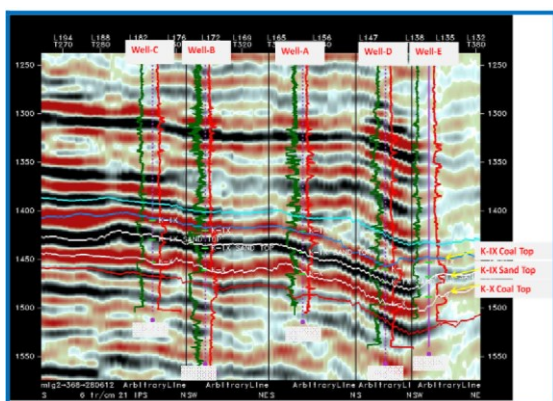


Fig 7: Arbitrary line from seismic data passing through different wells in the area.

It has been observed that the thickness of reservoir in this area is around 2-8 m. The dominant frequency in the study area is around 25-30 Hz. and average velocity is around 2500 m/s in sand hence, thin pay reservoirs in this area are beyond seismic resolution. Acoustic impedance contrast, reflector spacing and variation of these parameters determine the seismic response of a stratified system. In the presence of thin stratified layers, the amplitude maxima or minima never correspond to a particular interface and composite response is generated. Strong impedance contrasts at boundaries have predominant influence on the reflection pattern. High impedance contrasts of coal is masking (influencing) the seismic response of thin reservoir K-IX sand.

Structure Mapping:

The time map of K-IX sand top is shown in (Fig.8) where a major low (Nardipur Low) is seen separating the Kalol and Limbodra Fields. Most of the drilled wells of the study area are seen falling on the flank of this low.

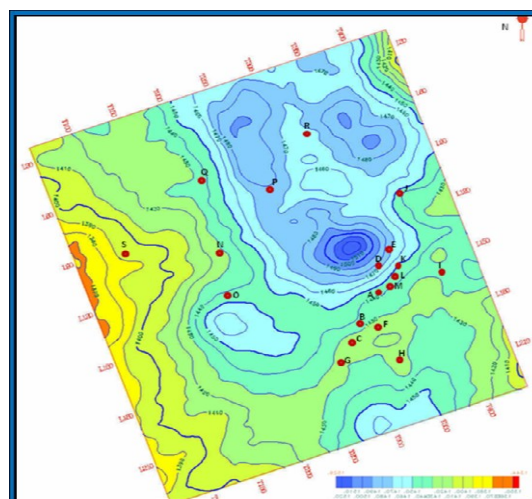


Fig8: TWT map on top of K-IX sand showing the Nardipur Low and well location in the field.

TWT thickness map between K-IX Sand top to K-X Coal top was prepared. This includes main pay reservoir of K-IX along with thick shale/silty shale and intermittent coals below. The map indicates a number of depo-centers which ranges from 10-40 ms trending mainly in the N-S direction. The deposition of K-IX lithounit as seen from the map was mainly through distributary channels and associated crevasse splays in bay fill area.

Porosity Estimation through Seismic guided log property mapping

In order to see the feasibility of impedance based discrimination between different lithofacies, crossplots between P-impedance (AI) and GR log were generated for all the wells in the data base. It was observed that though coal could be separated out easily, it was not possible to discriminate sand from shale. However, occurrence of low impedance is mainly due to coal and at times due to sand, but occurrence of high impedance is solely due to shale (Fig.9).

Model based seismic inversion was performed with initial model from calibrated wells. Total 13 nos. of wells of Limbodra field and 4 nos. of wells of Kalol field and part of Nardipur Low area, were taken for inversion.

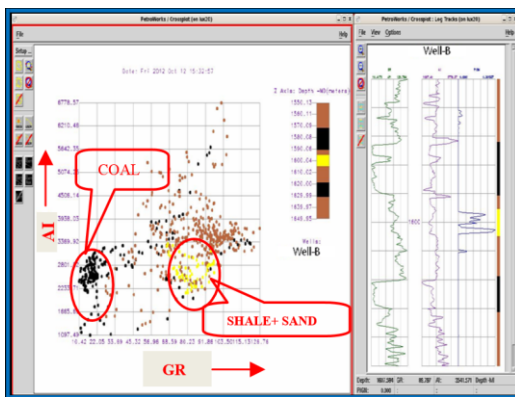


Fig9: Cross-plot between GR-AI of well-B.

Initially statistical wavelet was extracted for carrying out well to seismic correlation and finally the correlation was fine tuned by deriving composite wavelet extracted from wells and seismic. Correlation of about 80% (Fig.10) was achieved in most of these wells, which were further incorporated for initial model building along with the horizons corresponding to K-IX and K-X coal tops and top of K-IX pay sand.

Before running inversion on the complete volume, inversion QC was done to compare different parameters mainly with the predicted and original impedance curve. Error plots were analysed (Fig.10) which were generated from difference of synthetic trace from impedance and input seismic data.

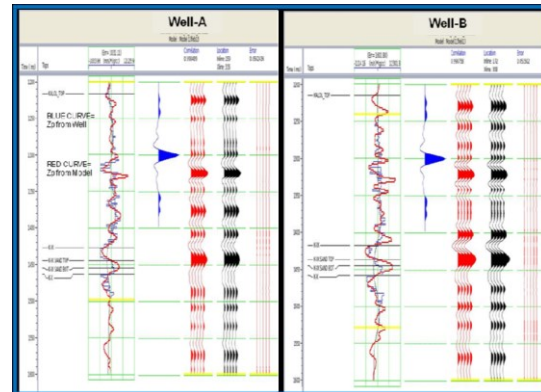


Fig10: Correlation and Error plot analysis of Inversion for Well-A and Well-B.

Finally, the seismic data was inverted to get impedance output for using it in further application for porosity estimation. Arbitrary line (Fig.11) passing through wells Well-A and Well-I taken from inversion cube, overlaid by computed P-impedance at well location, depicts that the reservoir facies just below the K-IX coal have moderately high impedance than coal layer above and lower impedance than the shale layer below. The acoustic impedance is not showing adequate separation between reservoir and nonreservoir facies.

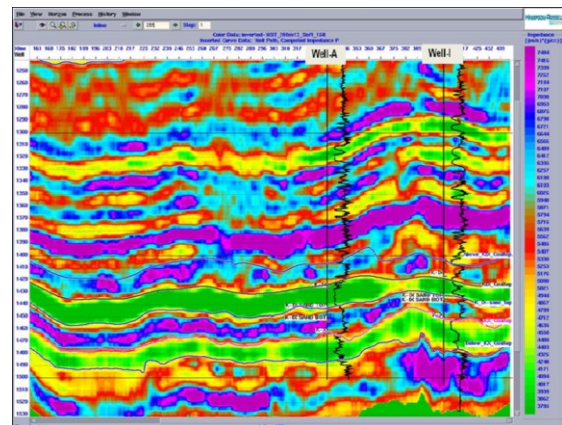


Fig11: Arbitrary line from model based impedance cube passing through wells of Limbodra Field with computed P-impedance overlaid at well location.

Multi-Attribute Linear Regression:

Multi-attribute transform, involves step wise linear regression approach in which covariance matrix is used to predict the parameter from a linearly weighted sum of the input seismic attributes. Weights are determined by Least Square optimization and are used for estimating the convolution filter operator which is applied to seismic data

to generate the reservoir property volume (Hampson, D.P et al., Geophysics 200, Vol. 66, No.1).

The impedance volume so generated was also used for multi-attribute analysis. Final processed effective porosity logs were chosen as target log which were used in porosity estimation from 3D seismic data. Porosity was estimated by application of linear and non-linear regression methods.

Target	Final Attribute	Training Error	Validation Error
1 Porosity	Integrate	0.032555	0.034390
2 Porosity	Amplitude Weighted Phase	0.030625	0.033338
3 Porosity	Dominant Frequency	0.029870	0.033200
4 Porosity	Average Frequency(Inverted-WST 28Feb13 S	0.028682	0.032315
5 Porosity	Filter 45/50 -55/60(Inverted-WST 28Feb13 So	0.028041	0.032576
6 Porosity	Filter 45/50 -55/60	0.027250	0.032802
7 Porosity	Filter 55/60 -65/70(Inverted-WST 28Feb13 So	0.025581	0.032714
8 Porosity	Cosine Instantaneous Phase(Inverted-WST 24	0.023958	0.032427
9 Porosity	Integrated Absolute Amplitude(Inverted-WST	0.025512	0.035490
10 Porosity	Amplitude Envelope(Inverted-WST 28Feb13 S	0.024839	0.034468

Fig12: List of Attributes used for Multi Attribute Regression.

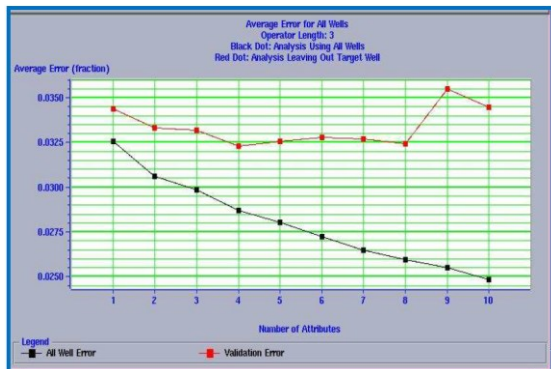


Fig13: Validation vs. Prediction Error curve.

It was observed that 8 numbers of seismic attributes with 3 point convolution transform operator shows minimum validation error of 0.032 in porosity estimation (Fig.12). The list of attributes used for porosity estimation and their respective training and validation error are shown in (Fig.13). Crossplot of Predicted versus actual porosity from the log shows 72% correlation in the reservoir zone (Fig.14). The Multi attribute transform through linear regression method shows relatively low predictivity which can be improved by non linear regression methods.

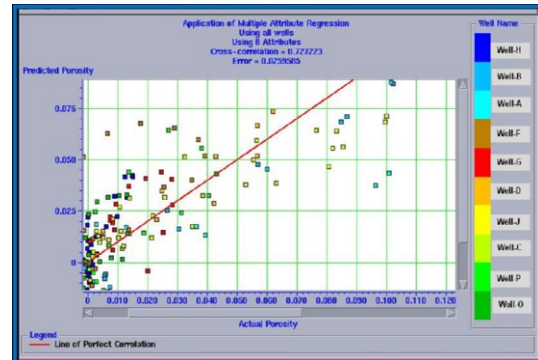


Fig14: Cross plot between Predicted vs. Actual porosity from Multi Attribute Analysis.

Multi-Attribute Non Linear Regression (PNN)

The multi attribute transform using Probabilistic Neural Networks (PNNs) is a mathematical interpolation scheme which uses neural network architecture for its implementation. In PNNs approach the weights are calculated using the concept of “distance” in attribute space from known point to an unknown point. The basic idea behind PNNs is to use set of one or more measured values (independent variables) to predict the value of single dependant variable. In practice, use of PNNs can be divided into four steps:

- Stepwise multi linear regression analysis and its validation
- Training neural networks to establish the non-linear relationship between seismic attributes and reservoir properties at well locations
- Apply trained neural networks to the 3D seismic data volume
- Validate results on wells by dropping one well at a time and predicting it from other wells.

Effective porosity of K-IX reservoir is estimated by using eight seismic attributes, three point convolution operator and PNNs using 10 wells (Well-O, P, C, J, D, G, F, A, B and H). Seismic attributes and convolution operator optimized during multi attribute analysis was taken for neural network training. It was observed from application/validation of neural network transform that the predicted porosity in the target zones was well corroborated with the actual porosity. The observed correlation coefficient and average error in porosity prediction were 0.98 and 0.006 respectively for training (Fig.15).

Neural network transform was applied to input seismic data for creating porosity volume. The Inline passing through Well-B (Fig.16) from the study area shows porosity variation across the section. Fig.17 shows the arbitrary line generated over porosity volume passing through the key wells of the Nardipur low.

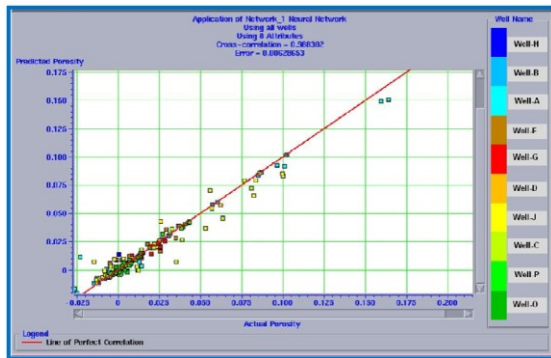


Fig15: Cross plot between Predicted vs. Actual porosity from PNNs.

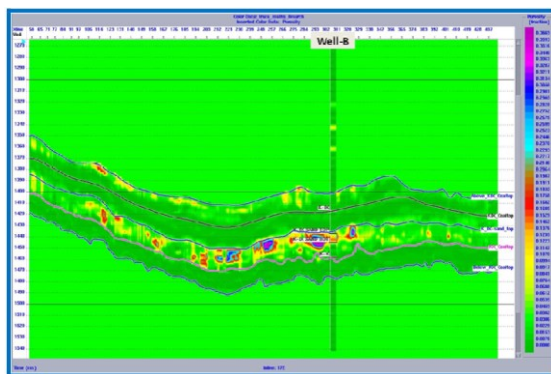


Fig16: Inline from porosity cube passing through Well-B overlaid with porosity log.

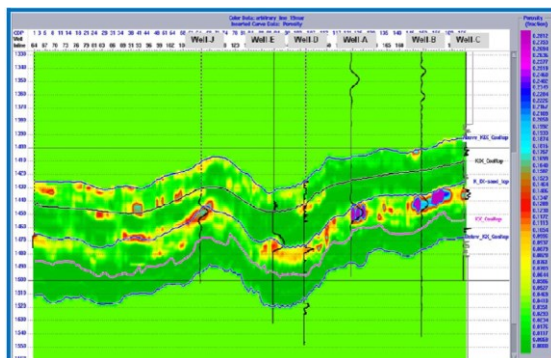


Fig17: Arbitrary line from porosity cube created using PNNs passing through key wells of Nardipur Low.

Porosity log overlaid at well location.

Arithmetic mean Effective porosity slice (Fig.18) was generated from the porosity volume in the target zone i.e. K-IX sand top, taking a window of 12ms. This slice was generated to show the spatial distribution of reservoir facies. It is observed that this map explains the status of drilled wells in the area with an exception of Well-S. The effective porosity map in conjunction with other map(s) (time thickness) generated during the study explains the distribution of reservoir facies.

Effective Porosity Model and Depositional environment

Based on the analysis of log motifs of the wells, review of available literatures and reports (both published and unpublished) in the public domain, it has been envisaged that independent channel(s) trending north-south flowed in the area. The identified channel(s) range from a few tens of meters to a few hundred meters in width and are separated by floodplains consisting of vegetated islands, natural levees and wetlands which are shallower away from the main channel and constitute the bay fill deposits. These distributary channel fills consist of fine to very fine sandstone/siltstone and are oriented sub parallel to depositional dip.

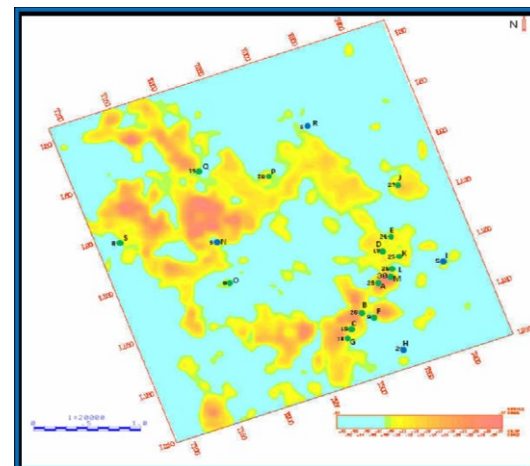


Fig18: Porosity map on top of K-IX-sand.

In the pay zone of K-IX, the sands encountered are thin, lenticular and discrete in nature, mostly representing crevasse splays and distributary channel fills. Reservoir quality in the study area is generally poor to good. The porosities range from 10 to 30% and the permeability tends to increase with increasing sand body thickness. The



highest permeability and thickness may be obtained where crevasse splay facies are concentrated.

The locales of high effective porosity (porosity pods) belong to subset of channel sand dispersal pattern which may not reveal complete geometry of the channel system. The channel sand distribution pattern was also influenced by winnowing action of tidal fluctuations in lower delta plain. The distributary channel(s) show branching geometry facilitating formation of porosity pods in its course. The Inversion and Probabilistic Neural Network (PNN) studies were attempted to generate the porosity distribution within sand facies and to bring out an effective porosity model. The effective porosity model so brought out in the present study reveals two main porosity pods, one around wells K, L and M and another around wells F, C and G which are conspicuous in their presence along with other porosity pods of Well-E and Well-J (Fig.18).The porosity model clearly brought out the different parts of the distributary channel fill and bay fill deposits. The expected reservoirs are mostly stratigraphic in nature; hence the reservoir pool may be isolated.

Conclusions

The main objective of the study was to generate effective porosity volume for detailed reservoir characterization of the area.

Post stack inversion was carried out using G&G data of all available wells in the area of study. Using this volume, effective porosity was predicted through Probabilistic neural network approach. The volume generated honour the results of drilled wells. Using effective porosity volume, horizon slices corresponding to K-IX pay sands were generated for redefining the spatial distribution of porosity pods. This study and its outcome may serve as a guide for further development of the area.

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