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Application of Multiattribute analysis for delineations of high impedance sands: a case study of Cambay basin

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Summary

In the present study, an attempt has been made to analyse the sand distribution pattern and nature of reservoir sands by multi-attribute inversion technique based on Probabilistic Neural Network to predict reliable lithological variations at reservoir zone.

Introduction

The study area (Fig.1) lies in the JambusarBroach sub-block of Cambay Basin and forms a part of north eastern rising flank of Broach depression. The area is bounded on the north by Mahi river and Jambusar field in the south. The objective of the study is to know the sand dispersal pattern of Hazad pay sands. The log and testing data of six wells drilled in the area reveal that the Hazad sands are lenticular in nature. Therefore the Seismic Inversion study was done to know the extension Hazad pay sands.

Depositional Environment

A Deltaic system is envisaged in the study area. The sediments were mainly supplied by the inter distributary channel which was from northeast i.e. through Dabka – Gajera area. This inter distributaries areas form the part of the upper Delta plain which exist above the marine influence and generally dominated by alluvial depositional system. The log and testing data of six wells drilled in the area reveal that the Hazad sands are lenticular in nature. The sands occur as isolated lobes separated by interdistributory shale.

Methodology

3D seismic PSTM stack volume was used to generate attributes, Check shot corrected computed impedance logs of eight wells were taken as target logs. Post stack impedance volume produced through model based inversion algorithm was taken as external attribute, so that each well has training data in the form of target impedance log, composite seismic and impedance trace from seismic and impedance volume shown in Fig-3.

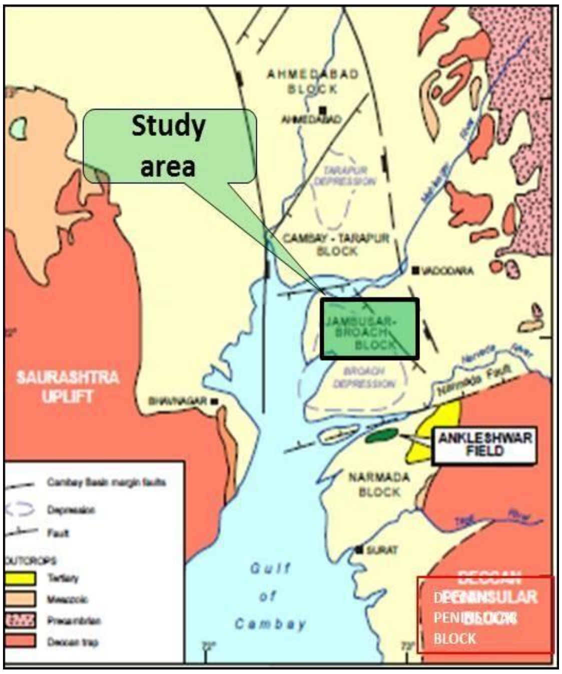

Figure 1: Location map of the area

The post stack model based inversion carried by us had given good result but it did not give enough temporal resolution to delineate the reservoir sands, so to improve

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the vertical and lateral resolution we used the combination of multi attribute with inversion through Probabilistic neural network training using Hampson Russell software Emerge to get high resolution impedance volume.

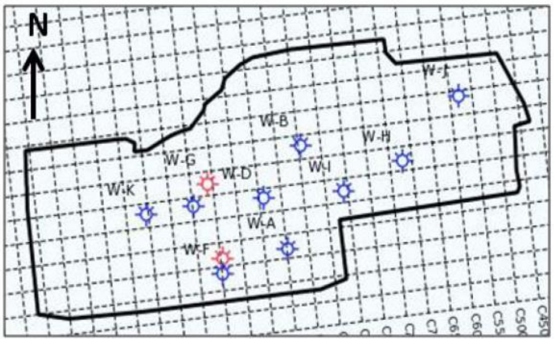

Figure 2: Base map showing wells

Serial No:	Well name	Well status
1	W-A	Abandoned
2	W-B	Abandoned
3	W-C	Gas
4	W-D	Abandoned
5	W-E	Abandoned
6	W-F	Abandoned
7	W-G	Gas
8	W-H	Abandoned
9	W-I	Abandoned
10	W-J	Abandoned
11	W-K	Abandoned

Table 1: Wells status of the study area

Steps of multiattribute stepwise regression method

The internal attributes are derived from seismic volume and the external attributes from impedance volume. The attribute generated are sample based, this mean it transform input trace in such way that the output trace contain the same number of samples (Daniel P. Hampson.. et al:2001)

- We find a suitable operator that can predict log properties from seismic attribute.
- In determining the attributes based on step wise regression procedure we found the best correlation come from single attribute inversion results shown in Table-2.

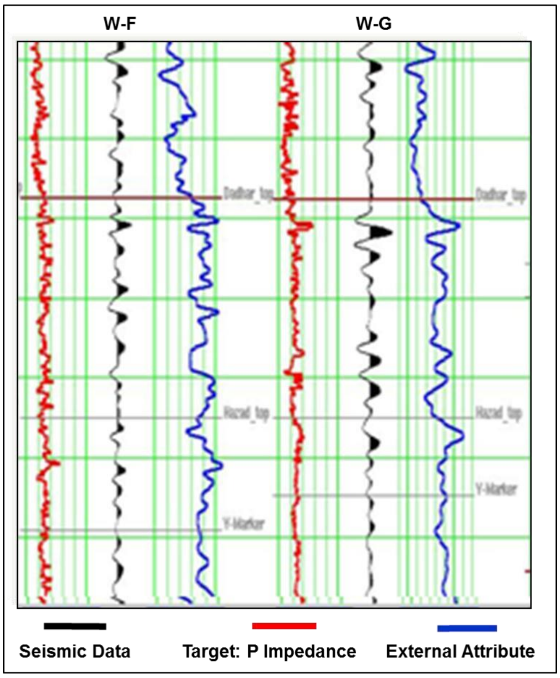

Figure 3: Training data for each well

- Second best correlation comes from integrate attribute that uses the inversion results and integrate as pair shown in row two of Table-2.
- Third best correlation comes from quadrature attribute which uses the combination of inversion results integrate and quadrature as best triplet shown in row three of Table-2.
- The fourth best correlation comes from raw seismic which is in combination of inversion results, integrate and quadrature attribute is best quadruplet shown in row four of Table-2.
- It is also observed that training error decrease with an increase of attributes however the validation error decreases to minimum and then again increases after fourth attribute.

Table 2: Attributes used for multiattribute analysis

SN	Target	Final Attributes	Training Error	Validation Error
1	P-Impedance	Inversion Results	499.64245	500.89598
2	P-Impedance	Integrate	491.51292	494.07925
3	P-Impedance	Quadrature Trace	488.50469	493.09466
4	P-Impedance	Raw Seismic	485.60055	490.3244
5	P-Impedance	Filter 5/10-15/20	485.28459	490.83861
6	P-Impedance	Filter 45/50-55/60	484.95316	490.88034
7	P-Impedance	Second Derivative Instantaneous Amplitude	484.74479	490.72341
8	P-Impedance	Cosine Instantaneous Phase	484.57834	490.72959

It is further concluded that four attributes are actually enough to predict the target logs and including more attribute could degrade our result shown in Fig-4 .We have generated plots to showing that how well the prediction can been done using four attribute and single point convolution operator as shown in Fig-3, Fig-4. We have generated several diagnostic QC-plots to validate the results of multiattributes analysis through stepwise regression method.

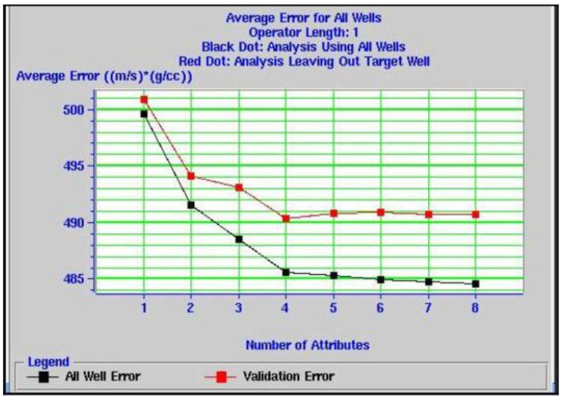

Figure: 4 Multiattribute analysis errors.

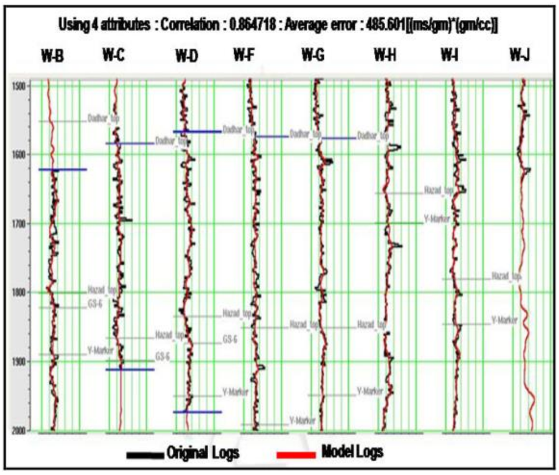

Figure: 5 Multiattribute analysis training results

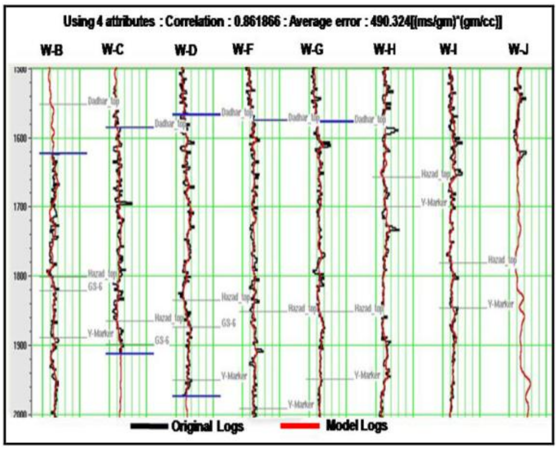

Figure: 6 Multiattribute analysis Validation results

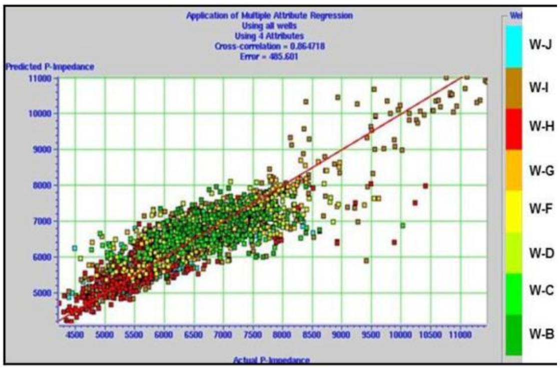

Figure: 7 Cross plot predicted computed impedance curves & borehole computed impedance curves (multiattribute analysis)

Figure: 8 Multiattribute analysis: average error at each well

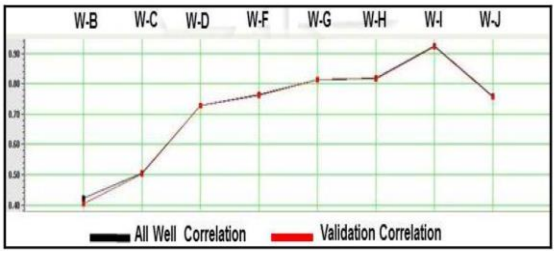

Figure: 9 Multiattribute analysis: average correlation at each well

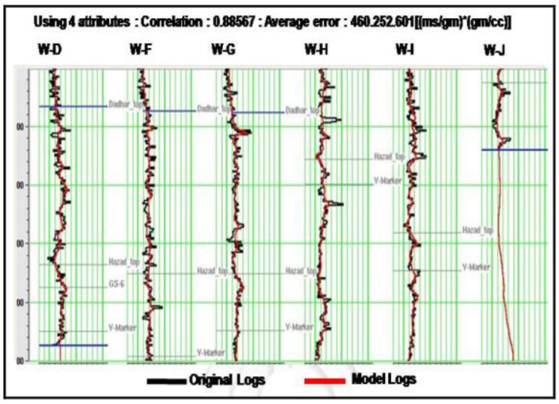

Figure: 10 Probabilistic neural network: Training results

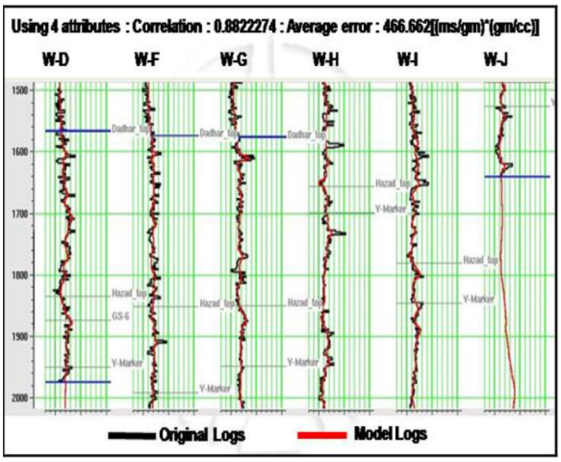

Figure: 11: Probabilistic neural network: validation results

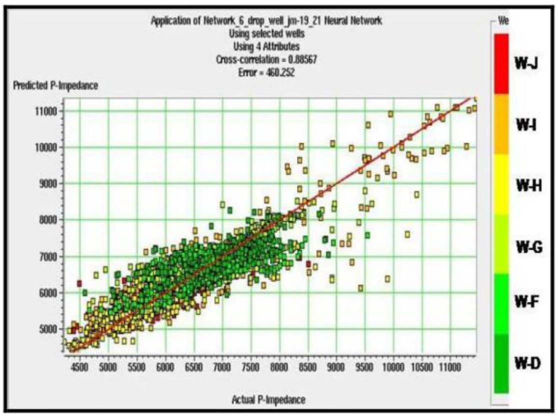

Figure: 12 Cross plot of predicted computed impedance curves & borehole computed impedance curves (PNN)

Results of multiattribute analysis regression based

Using multiattribute analysis to determine attribute stepwise regression has following observations.

Using four attribute, the training results shown correlation around 86%, while the average error is 485.6{(m/s)*(g/cc)} and the validation results shown correlation around 86%, while the average error is 490.3{(m/s)*(g/cc)} for model and original logs as shown in Fig-5, Fig-6 and Fig-7. These results further validated from average correlation and error of at each well as shown in Fig-8 & Fig-9, which shows that for well W-B and well W-C we found high RMS error and low correlation between predicted and impedance log curves based on these observation we have dropped two wells to get much better results.

Results of multiattribute analysis PNN based

Probabilistic Neural Network (PNN) was trained to find best non-linear relationship (Daniel J.et al.2001) between between four attributes i.e. Inversion results, Integrate, Quadrature trace, raw seismic and actual computed impedance logs for it was found that the PNN model has given higher correlation coefficient around 88%, while the average error is 460.2{(m/s)*(g/cc)} comes for the predicted logs shown in Fig-10

Cross-validation: In this mode we divided the entire data into the training data set and the validation data set, then the training data set is used to derive the transform, while the validation data set is used to measure its final prediction error. This is based on the assumption that overtraining on the training data set will result in a poor fit to the validation data set.

The training data set consists of training samples from all the wells, except specified hidden well. The validation data set consists of samples from that hidden well. We have repeated the process of cross validation, each time leaving out a different well to get the predict value of hidden well using the trained network so finally we get total validation error which is the rms error of individual error. (Daniel P. Hampson.. et al:2001) The validation results shown correlation about 88%, while the average error is 66.6{(m/s)*(g/cc)} for predicted logs and original impedance logs shown in Fig-11 and the results are further validated by the crossploting predicted computed impedance curves against borehole computed impedance curves (PNN) shown in Fig-12 .

On the basis of above results we have decided to carry out probabilistic neural network (**PNN**) based inversion for our study area to map the lateral instability and strong heterogeneity of sand distribution at the reservoir level *(Liu Jinping*., et al 2009)

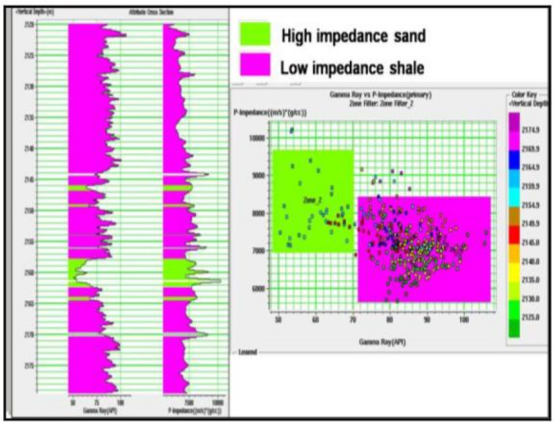

Figure: 13 Log property cross plot

Results and discussion

Analysis of log properties through cross plot

- We have crossplotted gamma log against computed impedance obtained from sonic and density log. The gamma log is being used to discriminate between sand and shale.
- The correlation of GR and Impedance logs shows that reservoir sands are having high impedance and overlying shales are having low impedance.

Interpretation: The inversion and cross plots studies suggest that the pay sand shows high impedance whereas overlying shales are having low impedance shown in Fig-13 .The impedance slice and random line generated within the target zone shows three sand lobes separate by inter-distributary low impedance shales. This also collaborates with sand maps of the reservoir zone. Hence the seismic inversion clearly brings out the sand dispersal pattern (Fig-14) which was not possible by the normal seismic attribute studies. It is also observed from Fig-15 that the high impedance sand is having low rms amplitude which further validates our result.

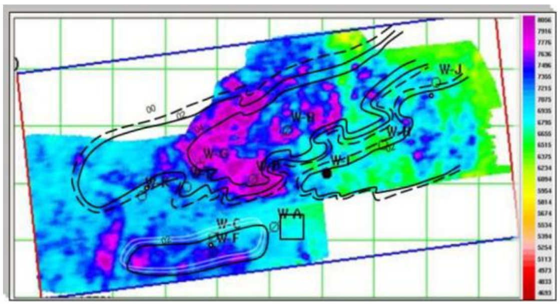

Fig 14: Sand map overlaid over impedance map

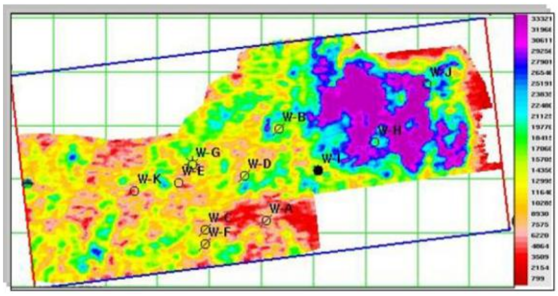

Figure-15: RMS amplitude average windowed horizon slice of 4ms i.e. 2 ms above and below Hazad Pay

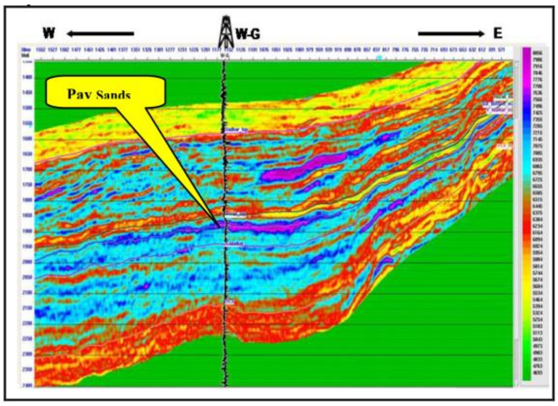

Figure-16: Acoustic impedance section (model Based)

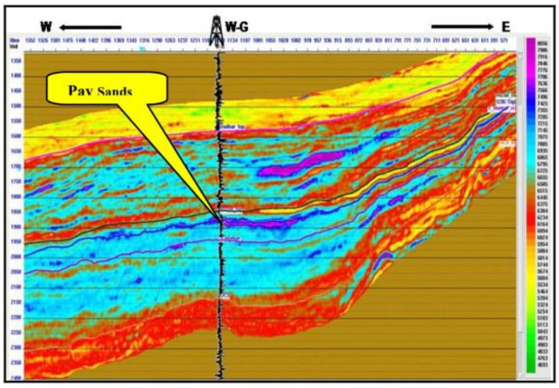

Figure-17: Acoustic impedance section (PNN based)

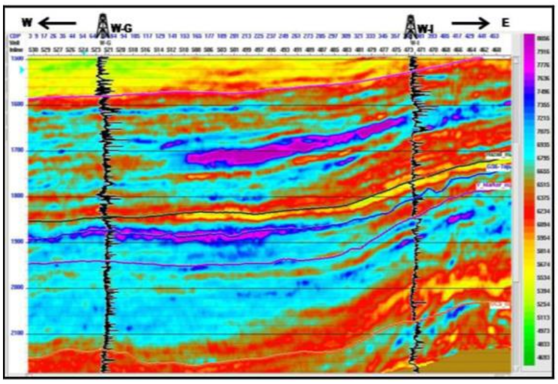

Figure-18: RC line through well w-G and W-I (PNN based)

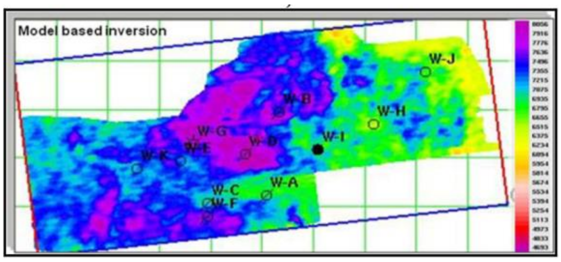

Figure-19: Impedance slice average windowed horizon slice of 4ms i.e. 2 ms above and below Hazad Pay (model based)

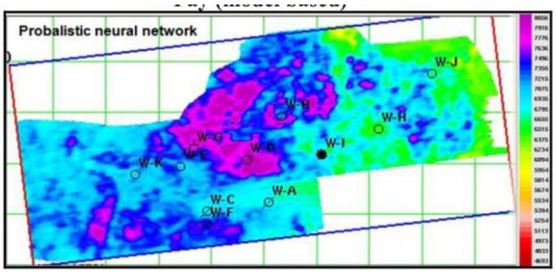

Figure-20: Impedance average windowed horizon slice of 4ms i.e. 2 ms above and below Hazad Pay(PNN based)

- It is concluded from the inverted sections shown in Fig-16 and Fig-17 that the inversion based on PNN has higher resolution as compared to model based inversion. The Results are further validated with impedance slices shown in Fig-19 and Fig-20, which clearly shows in map view that the lithological pattern from PNN shows a improved resolution over model based inversion and a better discrimination of high impedance sand and low impedance can be done
- Random line along impedance volume (PNN) between well W-G and W-I shown in Fig-18 shows there is a facies variation of high impedance sand to medium impedance which can be also be observed from horizon based windowed amplitude and impedance slice along hazad pay shown in Fig-15 and Fig-20.

Conclusion

- The integrated approach to interpretation adopted in this case study has resulted in precise mapping of the high impedance reservoir sand geometries.
- PNN based inversion has provided a better vertical and lateral resolution as compared to the model based inversion.
- Higher vertical resolution and accurate layer-bylayer lateral extrapolations of the acoustic impedance improved the stratigraphic interpretation, sedimentary architecture, and lithology prediction which were subsequently used to refine the drilling plan of new exploration

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N.B :The views expressed in the paper are solely of the authors and not necessarily of the organization in which they are working.