INNOVATIVE APPROACH FOR RESERVOIR CHARACTERISATION USING SOFT COMPUTING AND ALTERNATING CONDITIONAL EXPECTATION IN COMPLEX SCENARIO—A CASE STUDY FROM WESTERN OFFSHORE BASIN OF INDIA

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Summary

'As complexity increases precise statements lose meaning and meaningful statements lose precision'...Lotfi Zadeh, inventor of fuzzy logic.

Earth scientists are confronted with the need to deal with many diverse data types which come from a wide variety of sources having different scales, different degrees of imprecision and uncertainty. To combat this problem, it is usual to attempt to process the data to the point where application of our precise algorithms can give a reasonable answer. A second alternative would be to preferentially employ methodologies that are tolerant to the imprecision in the input data with it.

Soft computing offers an excellent opportunity to address the following:

a) Integrating information from various sources with varying degrees of uncertainty
b) Establishing relationships between measurements and reservoir properties
c) Assigning risk factors or error bars to predictions.

Neural networks have been used extensively in the oil industry. It serves as an integrator of the information. An artificial network consists of a pool of simple processing units, which communicate by sending signals to each other over a large number of weighted connections. Each unit performs a relatively simple job: receive input from neighbors or external sources and use this to compute an output signal, which is propagated to other units. Apart from this processing, a second task is the adjustment of the weights.

Non-parametric regression technique, such as ACE (Alternating Conditional expectation) is also used in the present study to estimate saturation in the reservoir from other attributes. ACE does not requires a functional form to be presumed a priori for the regression thus reducing the problem to that of estimation of a set of parameters.

Introduction

The study area is from a producing field of Western offshore Basin of India (Fig.1). Pay sands are too thin (2 to 6m mostly) to be resolved with available seismic peak frequency. Both Oil and gas have been found in this area, in Oligo-Miocene discrete sandstone reservoirs deposited in deltaic (Tide dominated system) environment. Due complex nature of reservoir sands, it is very difficult to investigate them with any deterministic method from seismic data. Soft computing and statistical approach has been adopted to predict density and saturation map. Density has been estimated first from other seismic attributes and impedance data through multi-attribute regression and probabilistic neural network applications. Better version of this output was then subjected to Alternating Conditional expectation (ACE) along with other attributes to generate saturation map at reservoir level.

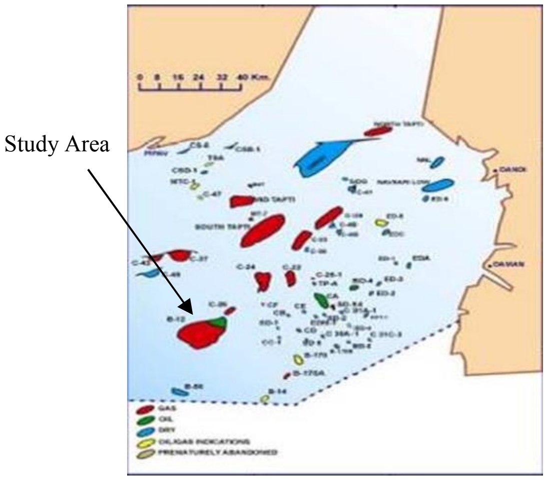
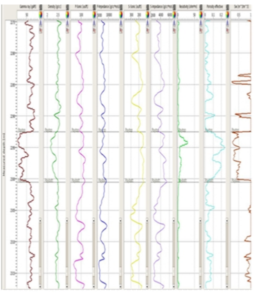


Fig.1 Base Map showing area of interest

Multi Attribute Analysis for Reservoir Characterization- A Case Study

Methodology:

These pay sands show low impedance contrast with reference to enclosing shale and are not discernible on the normal amplitude and P-impedance volumes. Thick, water bearing sands, on the other hand show bright amplitude anomalies. Due to the above factors, non-bright spot seismic response of pay sands are only expected, if at all perceptible seismically. AVO response of such thin & low contrast gas pay sands is also too low relative to single isolated interface response in Intercept-Gradient space (Fig.2). P-impedance is not suitable for distinguishing pay from non-pay. However density seems to be relatively preferable petrophysical parameter for distinguishing between pay sands and rest of the clastics as shown by crossplotting of density and gamma ray logs (Fig.3). An attempt was made to delineate pay sands in the area within the clastic formation through prediction of density and gas saturation from multiple seismic attribute though multi-attribute linear regression, neural network based prediction and Alternating conditional expectance (ACE) approach.



Pay Top

Elastic parameter	Above	Below	Unit
P-Impedance	7315	7693	g/cc*m/s
S-Impedance	3632	4030	g/cc*m/s
Density	2.45	2.42	g/cc

Pay Bottom

Elastic parameter	Above	Below	Unit
P-Impedance	7693	7179	g/cc*m/s
S-Impedance	4030	3500	g/cc*m/s
Density	2.42	2.45	g/cc

Amplitude variation with angle for gas sand top and base do not show expected Class-II/III type variation

Fig.2

Fig.2 Amplitude variation with angle for gas sand top

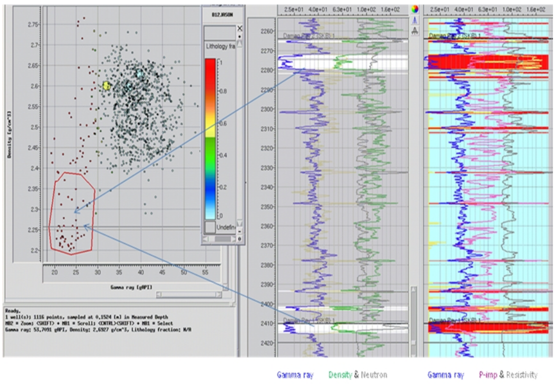


Fig3. CROSSPLOT OF DENSITY VS GAMMA RAY FROM WELL DATA SHOWS PAY SANDS ARE DISCRIMINATED BY LOW DENSITY

Blue color Log = Gamma Ray Log
Green color Log = Density Log

Traditional methods are computationally formidable and have consistently failed to interpret this sort of data in an autonomous manner. Therefore, there is a need for application of the state of art data analysis methods based on Probabilistic, Fuzzy and multidimensional geometry in this field.

The aim of the study is to use effective data-driven methods to combine and infer as far as possible complete description of reservoir characteristics. Unfortunately, only linear and simple nonlinear information can be extracted from these data by standard statistical methods. As an alternative, neural networks and fuzzy logic have the potential to establish a model from nonlinear, complex, and multi-dimensional data and find wide application in analyzing experimental, industrial, and field data.

In the neural network, the neurons or the processing units may have several input paths corresponding to the dendrites. The units combine usually by a simple summation, that is, the weighted values of these paths (Fig. 4). The weighted value is passed to the neuron, where it is modified by threshold function such as sigmoid function. The modified value is directly presented to the next neuron.

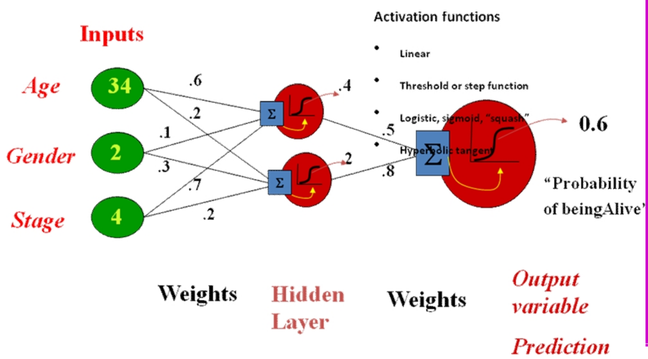
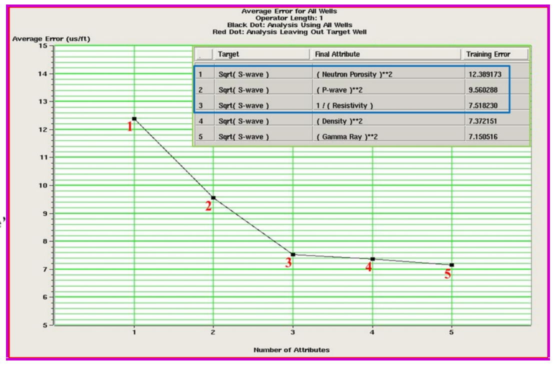


Fig4:Example of Neural Network Model



In the present case the density has been estimated from other seismic attributes and impedance data through multi-attribute regression and probabilistic neural network applications. Better version of this output then has been subjected to a technique called Alternating Conditional expectation (ACE).

In general, regression problem involves a set of predictor and a random variable called response variable. We try to explain the effect of one or more independent variables (predictors or covariates) on a dependent variable (response).The aim of regression analysis is to estimate the conditional expectation E(Y|X1,X2,……). Conventional multiple regressions requires a functional form to be presumed a priori for the regression thus reducing the problem to that of estimation of a set of parameters. Success of this approach lies in the appropriateness of the assumed model. Unfortunately traditional multiple regression techniques are limited in this respect since they usually require a priori assumptions about the functional forms that relate the response and predictor variables. When the relationship between the response and the predictor variable is unknown or inexact, which is frequently the case for reservoir rocks and petrophysical properties, parametric regression can yield erroneous and misleading results. Non-parametric regression technique, such as ACE (Alternating Conditional expectation) can provide more suitable approach in such situation.

Here, we used the ACE algorithm developed by Breiman and Friedman (1985) for estimating optimal transformations for both response and independent variables in regression and correlation analysis. The power of the ACE approach lies in its ability to recover the functional forms of variables and to uncover complicated relationships. The non-parametric transformation technique generates regression relation in a flexible data defined manner and in doing so let the data suggest the functionalities.

The non-parametric approach adopted by GRACE program, as used here, generates a transformed value corresponding to each data point for the dependent and independent variables. However, it does not give a functional form for these transformations. In order to generate a functional form for the final correlation, one must fit these transformations using appropriate functions. Simple polynomials are generally good enough to fit these transformations. This is accomplished using the EXCEL macro.

In seismic reservoir characterization, it is important to formulate how 3-D seismic information (attributes) is related to reservoir parameters, lithology and geology as well as well logs (e.g. porosity, density, etc.). 3-D seismic data is transformed to reconstruct the 3-D volume of relevant reservoir information away from the wellbore. Workflow adopted for this study is presented in Fig5. To start with, five attribute viz. P-impedance, Band pass filtered data, dominant frequency, instantaneous. amplitude and amplitude derivative have been used as input to neural network to predict density volume after extensive training and validation at the well locations (Fig.6). In the present case the density has been estimated through multi-attribute regression and probabilistic neural network applications. Better version of this output then has been subjected to Alternating Conditional expectation (ACE). Zone of interest can be seen on the section display through all the wells (Fig7). Map of density distribution at target level of sand30 has been prepared (Fig.8) from estimated density data.

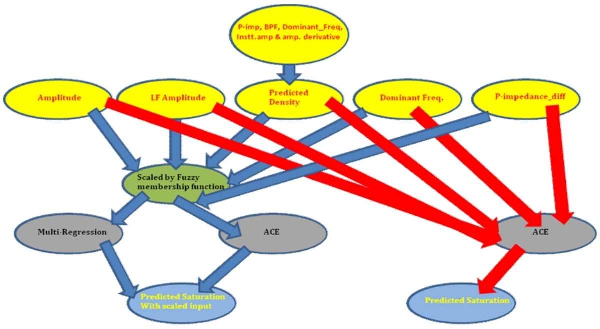


Fig.5

Rock physics analysis and feasibility studies

Objective of the rock physics analysis is to determine the pore-fluid sensitivity of different elastic parameters. Analysis through histogram and cross plot of P-impedance and Vp/Vs logs were carried out to find the desired separation for different litho-fluid types. Histogram of P-impedance and Vp/Vs logs in the zone of interest was generated (Fig. 8). On the basis of only P-Impedance, It is difficult to separate hydrocarbon and non-hydrocarbon bearing zones, while histogram of Vp/Vs shows most likelihood of occurrence of hydrocarbon bearing zones is in low Vp/Vs range. Cross plot of P-impedance and Vp/Vs logs for zone of interest shows moderate to slightly high P-impedance and low Vp/Vs for hydrocarbon producing wells.

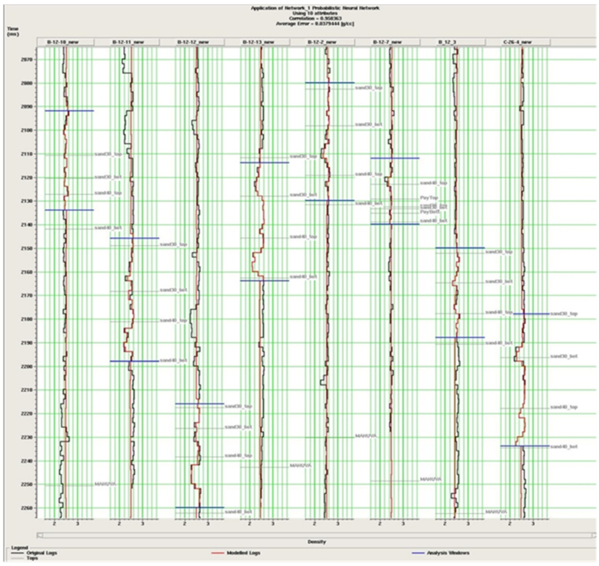


Fig6:Network prediction within the target window

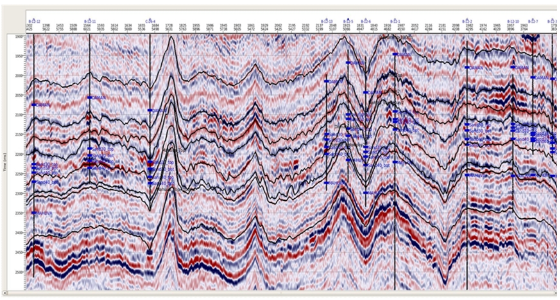


Fig7.Arbitrary line of PSTM stack through wells (picked horizons superimposed) zone of interest:san30 layer

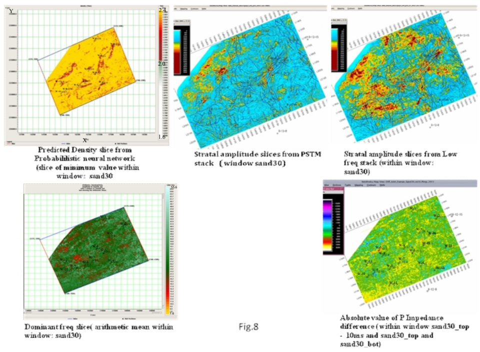


Fig.8

	Dom Freq.			Density			Pimp. Diff.			PSTM amp.			LF amp.			Peak spec. freq.		
	Well		Full Ran	Well		Full Ran	Well		Full Ran	Well		Full Ran	Well		Full Ran	Well		Full Ran
	Gas	Dry		Gas	Dry		Gas	Dry		Gas	Dry		Gas	Dry		Gas	Dry	
Max	40.5	41.0	54.28	2.5	2.5	2.62	935.7	549.7	2433.2	2711.8	2697.8	9344.1	3148.6	4240.1	8365.2	37.4	50.6	60.6
Min	16.3	17.7	8.47	2.2	2.1	1.6	42.8	69.1	0.0	1227.5	949.6	58.1	1558.8	398.2	26.3	15.4	14.6	0
Mean	27.6	30.5	28.35	2.4	2.4	2.44	268.3	278.3	239.0	1895.5	1607.7	1865.76	2343.7	2552.7	2386.29	26.3	28.5	27.02
Median	25.3	30.6	28.10	2.4	2.4	2.45	154.1	278.6	192.6	1781.6	1435.1	1728.5	2430.3	2873.3	2345.2	28.9	26.7	28.8
St. dev.	7.608845	8.19	6.30	0.103086	0.115	0.07	298.69	175.23	201.3	524.28	674.94	891.91	537.989	1169.13	927.55	8.17	11.79	8.83

Fig9: Statistical data for constructing membership diagram

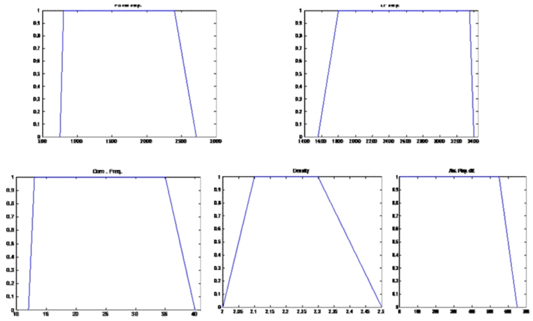


Fig.10:Membership diagrams for different seismic attributes for gas wells

Concept of Fuzzy membership of different input is introduced at this stage. Membership diagram shows the different degree of membership of the members of fuzzy set. Here for constructing membership diagrams we use the mean value and standard deviation value of different attributes for Gas wells. In general we have used (Mean ± n*Stan. Dev), where n is 1 or 2.Thus Membership diagram is a sort the window having favorable range of attributes for low amplitude gas sand (snad30) level. Different Weights of different attributes are obtained on the basis of respective membership functions derived from well data. Then the average and multiplications of weights of attributes is calculated as shown in Fig9. Trapezoidal Membership functions as shown in Fig.10 have been used for different seismic attributes for gas wells (e.g. PSTM amplitude, LF amplitude, Density, Dominant Frequency and P-impedance). Different Weights of different attributes are obtained on the basis of respective membership functions. Then the average and multiplications of weights of attributes is calculated (Fig11). Scaling the PSTM, LF amp and Density attribute by average weight and weight multiplication as shown in fig 12 (Example here is for density only). Both scaled and unscaled input maps are subjected to Linear Regression and ACE.

Linear Regression Relationship used for Gas Saturation Prediction is:

$$\text{Predicted Gas Saturation} = \text{PSTM} * 0.0089 + \text{LF} * (-0.0045) + \text{DomFreq} * (-2.0051) + \text{Density} * (-245.099)) + \text{DiffPimp} * (-0.0777) + 1 * 683.8785$$

For ACE application GRACE program has been used. The non-parametric approach adopted by GRACE program generates a transformed value corresponding to each data point for the dependent (saturation) and independent variables (membership function scaled/unscaled input attributes). In order to generate a functional form for the final correlation, one must fit these transformations using appropriate functions. Simple polynomials are generally good enough to fit these transformations. This is accomplished using the EXCEL macro (Fig.13). ACE transform plot for density is shown in Fig.14.

ACE transform relationships - After fitting polynomials to these transform curves we get following relationships:

1.
$$\text{Density\_Trans} = -56.53 + 60.08 * \text{density} - 15.2498 * \text{density} * \text{density}$$

2.
$$\text{Pimpdiff\_Trans} = 0.989936 - 0.003886 * \text{Pimpcdiff} + 0.0000003387 * \text{Pimpdiff} * \text{Pimpdiff}$$

3.
$$\text{Dom\_Freq\_Trans} = 1.614 - 0.0278 * \text{Domfreq} - 0.001252 * \text{Domfreq} * \text{Domfreq}$$

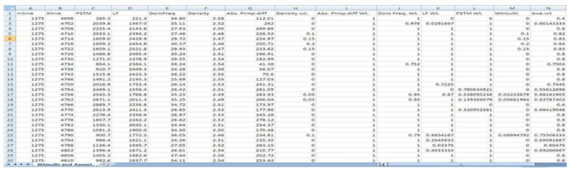
4.
$$LF\_Trans = 1.3608 - 0.000849 * LF + 0.00000012186 * LF * LF$$

5.
$$\text{PSTM\_Trans} = -0.3343 - 0.000126 * \text{PSTM} + 0.00000015183 * \text{PSTM} * \text{PSTM}$$

6.
$$\text{Sat\_Trans} = 1.031689002 * \text{Sum\_tr\_indep} + 0.00000146205$$

7.
$$\text{Intermediate Sat} = 34.93549625 + 24.46345571 * \text{Sat\_tr} - 2.383288878 * \text{Sat\_tr} * \text{Sat\_tr}$$

8 .
$$\text{Predicted Sat} = 0.9555457968 * \text{Intermed.Sat} + 1.651236434$$



	Inline	Xline	PSTM	LF	DomFreq	Density	Abs. Pimp.diff	Density wt.	Abs. Pimp.diff Wt.	Dom Freq. Wt.	LF Wt.	PSTM Wt.	Wtmulti	Ave.wt
2	1275	4698	285.2	221.3	34.80	2.58	112.01	0	1	1	0	0	0	0.4
3	1275	4702	2039.8	1567.0	35.11	2.52	262	0	1	0.978	0.0291667	1	0	0.60143333
4	1275	4706	2255.4	2143.8	27.63	2.50	269.86	0	1	1	1	1	0	0.8
5	1275	4710	2033.1	2394.2	27.48	2.48	226.52	0.1	1	1	1	1	0.1	0.82
6	1275	4714	1609.0	2429.9	29.72	2.47	224.97	0.15	1	1	1	1	0.15	0.83
7	1275	4718	1609.2	2454.8	30.37	2.46	250.71	0.2	1	1	1	1	0.2	0.84
8	1275	4722	1609.1	2521.8	29.93	2.47	233.62	0.15	1	1	1	1	0.15	0.83
9	1275	4726	1486.8	2495.4	30.24	2.51	166.91	0	1	1	1	1	0	0.8
10	1275	4730	1271.0	2378.9	29.55	2.54	182.99	0	1	1	1	1	0	0.8
11	1275	4734	804.1	2364.1	36.24	2.54	41.38	0	1	0.752	1	1	0	0.7504
12	1275	4738	910.7	2449.3	24.28	2.56	36.07	0	1	1	1	1	0	0.8
13	1275	4742	1515.6	2423.3	26.22	2.55	75.6	0	1	1	1	1	0	0.8
14	1275	4746	1491.2	2195.3	25.69	2.55	127.03	0	1	1	1	1	0	0.8
15	1275	4750	2016.9	1733.4	26.14	2.53	241.31	0	1	1	0.7225	1	0	0.7445
16	1275	4754	2469.1	1556.4	26.42	2.51	281.09	0	1	1	0	0.780634921	0	0.55612698
17	1275	4758	2545.5	1768.8	35.25	2.49	283.93	0.05	1	0.95	0.87	0.538095238	0.02223679	0.68161905
18	1275	4762	2671.1	2011.3	35.25	2.49	266.04	0.05	1	0.95	1	0.139365079	0.00661984	0.62787302
19	1275	4766	2889.7	2238.8	34.72	2.51	173.97	0	1	1	1	0	0	0.6
20	1275	4770	2613.9	2411.3	26.65	2.53	177.96	0	1	1	1	0.320952381	0	0.66419048
21	1275	4774	2276.4	2356.6	26.97	2.53	245.28	0	1	1	1	1	0	0.8
22	1275	4778	1807.7	2242.2	26.82	2.52	278.12	0	1	1	1	1	0	0.8
23	1275	4782	1330.1	2045.1	34.64	2.51	254.37	0	1	1	1	1	0	0.8
24	1275	4786	1091.2	1900.0	34.50	2.50	170.48	0	1	1	1	1	0	0.8
25	1275	4790	900.7	1772.5	36.05	2.48	234.81	0.1	1	0.79	0.8854167	1	0.06994792	0.75508333
26	1275	4794	986.4	1621.1	34.26	2.51	235.35	0	1	1	0.2545833	1	0	0.65091667
27	1275	4798	1136.4	1565.7	27.05	2.52	263.15	0	1	1	0.02375	1	0	0.60475
28	1275	4802	1396.4	1671.2	26.61	2.54	210.77	0	1	1	0.4633333	1	0	0.69266667
29	1275	4806	1405.2	1882.6	27.44	2.56	202.72	0	1	1	1	1	0	0.8
30	1275	4810	982.6	1837.7	34.11	2.54	253.62	0	1	1	1	1	0	0.8

Wtmulti and Avewt.

Fig.11:Different Weights of different attributes are obtained on the basis of respective membership functions. Then the average and multiplications of weights of attributes is calculated

ANALYSIS OF RESULTS

Predicted gas saturation map at sand30 level with both linear regression and ACE method is illustrated in Fig.15. Fig16 demonstrates the difference of ACE output without and with scaling by respective membership function of input attribute. Features are better defined in the later. This makes it easier for the interpreter to decide on exploration / development location. Fig.17 shows the comparison between density predicted through Neural Network and gas saturation predicted through ACE which shows surprisingly good similarity. We finally validated all density and saturation values at well locations. Gas wells, viz. W-1, W-2, W-3 ,W-4, W-7 , W-8 , W-9, W-10, W-11 are in high saturation zone and Dry wells , viz. W-5 ,W-6 are in low saturation Zone. Predicting the saturation after scaling the input seismic attributes with respective membership function signifies filtering the attributes in the proper range which implies clustering the attributes sensitive to gas presence to enhance effect of saturation as shown in figure 16 and 17. Saturation map is superimposed on structural map at that level (Fig.18) for better understanding with reference to structural disposition.

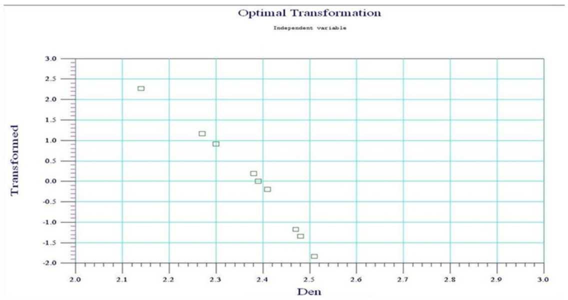
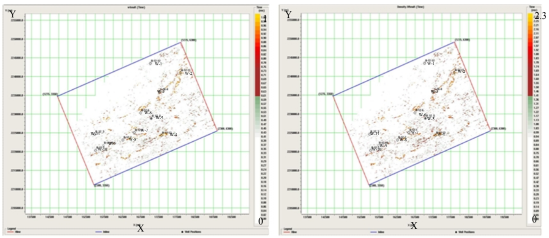


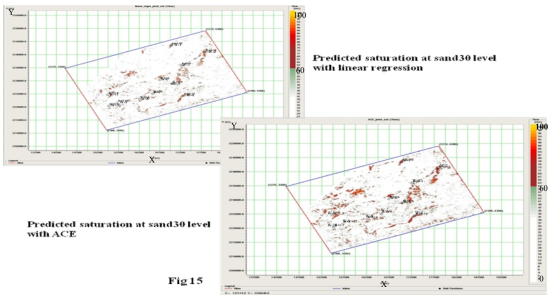
Fig 14. ACE Transform Plot From Grace



Plot for weight factors of different attributes.

Predicted Density scaled with multiplication of wt :window sand30

Fig.12



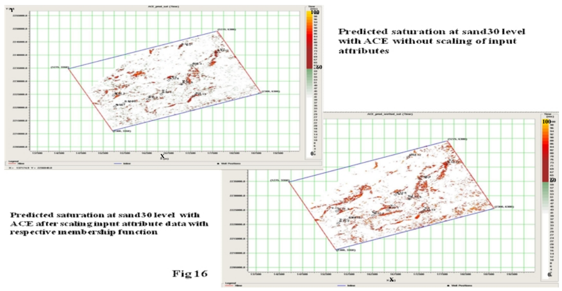
Predicted saturation at sand30 level with linear regression

Predicted saturation at sand30 level with ACE

Fig 15

2	Den	Den_Tr	diffPimp	diffPimp_Tr	DomFreq	DomFreq_Tr	Lfamp	Lfamp_Tr	Pamp.	Pamp._Tr	sat	sat_Tr	Sum_Tr_Indep	sat_Meas	sat_Calc_Inv_Tr
3	2.39E+00	2.39E-03	3.42E+02	-2.94E-01	2.98E+01	-3.45E-01	1.56E+03	3.38E-01	1.73E+03	-1.01E-01	2.49E+01	-4.10E-01	-3.99E-01	2.49E+01	2.51E+01
4	2.51E+00	-1.84E+00	1.31E+02	4.62E-01	1.63E+01	8.26E-01	2.45E+03	1.23E-02	1.83E+03	-5.93E-02	1.81E+01	-6.73E-01	-5.94E-01	1.81E+01	2.06E+01
5	2.30E+00	9.12E-01	4.28E+01	8.54E-01	2.48E+01	1.65E-01	2.74E+03	-6.10E-02	1.42E+03	-2.05E-01	7.18E+01	1.76E+00	1.67E+00	7.18E+01	6.98E+01
6	2.41E+00	-1.94E-01	8.51E+01	6.62E-01	2.53E+01	1.33E-01	2.66E+03	-4.62E-02	2.71E+03	4.36E-01	5.84E+01	1.13E+00	9.90E-01	5.84E+01	5.53E+01
7	2.27E+00	1.17E+00	9.36E+02	-2.35E+00	2.22E+01	3.77E-01	2.41E+03	2.64E-02	2.30E+03	2.04E-01	2.08E+01	-5.90E-01	-5.80E-01	2.08E+01	2.10E+01
8	2.48E+00	-1.34E+00	6.91E+01	7.35E-01	2.45E+01	2.04E-01	3.10E+03	-8.23E-02	1.39E+03	-2.13E-01	1.14E+01	-8.62E-01	-6.96E-01	1.14E+01	1.73E+01
9	2.47E+00	-1.17E+00	2.22E+02	1.24E-01	1.77E+01	7.17E-01	4.24E+03	-5.19E-02	9.50E+02	-3.13E-01	1.97E+01	-6.21E-01	-6.98E-01	1.97E+01	1.72E+01
10	2.14E+00	2.27E+00	4.50E+02	-6.69E-01	3.25E+01	-6.43E-01	2.68E+03	-5.17E-02	2.70E+03	4.28E-01	6.10E+01	1.25E+00	1.33E+00	6.10E+01	6.27E+01
11	2.38E+00	1.93E-01	1.27E+02	4.80E-01	3.96E+01	-1.43E+00	3.07E+03	-8.32E-02	1.55E+03	-1.77E-01	7.00E+00	-9.85E-01	-1.02E+00	7.00E+00	5.73E+00

Fig. 13 Tabular Data for Saturation Prediction with ACE



Predicted saturation at sand30 level with ACE without scaling of input attributes

Predicted saturation at sand30 level with ACE after scaling input attribute data with respective membership function

Fig 16

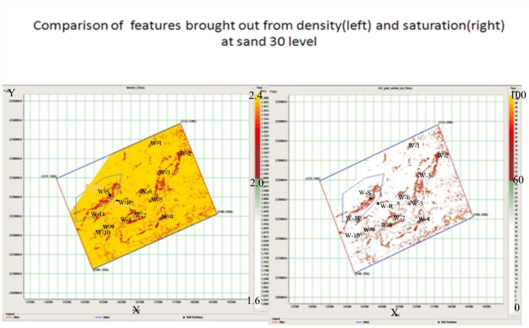
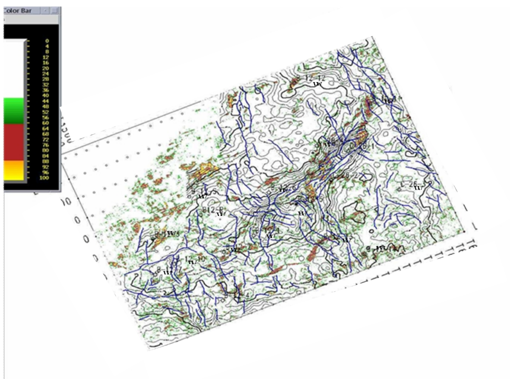


Fig 17



Saturation at sand 30 level with time structure map superimposed

Fig 18

CONCLUSION

The study is carried out to identify the gas bearing zone at sand30 level in an area of producing field of Western offshore Basin of India through Multi attribute linear regression and Alternating Conditional Expectation approach which is otherwise not possible to identify by direct hydrocarbon indicators (DHI), inversion and AVO analysis. On comparing the base map, computed density map and saturation map we finally conclude that all density and saturation values are validated at well locations.

Gas wells, viz. W-1, W-2 ,W-3 , W-4, W-7, W-8 ,W-9 , W-10 , W-11 are in high saturation zone and Dry wells , viz. W-5 , W-6 are in low saturation zone. Predicting the saturation after scaling the input seismic attributes with respective membership function implies clustering the attributes sensitive to gas presence to enhance effect of saturation. Areas of good saturation zone away from the drilled wells may lead to additional prospect locations within Sand 30 sequence. This zone is shown in polygon fitted area.

This study has established another innovative approach to find prospective areas at sand30 level by means of multi attribute analysis which was otherwise difficult through conventional methods.

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