3D Seismic Genetic Inversion for Reservoir Characterization and Prospects Identification

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Abstract: ***This study Examine the possibility of development of one of the fields in south Iraq. AL-Kumait oil field is conventional structural reservoir. In order to delineate the whole image of the structure and to explore for new prospect in this field. A 3D seismic survey is applied. Two formation considered in this survey we will focus on NahrUmr formation in this study. NahrUmr is a clastic reservoir contain 3 sand member identified by Wireline logging and core samples. Two wells drilled in this field KT_1 which is producing from the second sand member and KT_2 which contain only water. The picked horizon of the formation structurally interpreted. The aims of this study is to generate effective porosity cube based on inverted acoustic impedance cube and calculated effective porosity from well data to identify a good reservoir quality that can be considered as a new prospect. Genetic inversion of 3D seismic a patented Schlumberger product used as a method in petrel 2015 it uses a nonlinear multi trace operator to convert the seismic cube or its related attribute to a corresponding log property. A derived effective porosity from well logs of the two wells used to train the data and convert it to the porosity cube the result shows a good reservoir quality in two other closer and faulted area that can be a good new prospect.***

Keywords: Reservoir characterization, Genetic inversion, NahrUmr formation, 3D seismic.

1. Introduction

AL- Kumait oil field is located in Euphrates subzone a part of Mesopotamian basin in south Iraq (Ditmar, 1984) (Figure1-1).in this study we will focus on NahrUmr formation on of two major reservoir in this field . Three sand members categorized in this formation separated by shall beds. (Sand2) member considered as the best res property and produced oil in KT_1 well while in KT_2 contain only water. Due to importance of NahrUmr formation in containing hydrocarbon accumulations and its good reservoir properties in central and south of Iraq in the Mesopotamia basin. The formation is belonging to the Albian sub cycle deposition sequence it's defined by Glynn Jones in 1984 from Nahr_Umr structure south Iraq [5]. Major tow depocenters in central and S Iraq they receive clastic sediment from Rutba uplift and Arabian shield and it's considered as Clastic - Carbonate inner shelf facies [5]. NahrUmr is very important reservoir in 37 structures in south Iraq [2].Bothe contact of the formation are conformable in Iraq [5].in this field NahrUmr well sections where limestone and shall alternating in most upper part from the formation then change to shelly limestone rock in the middle then change to Sandston alternating with shall stone a three member of sand in well KT_1: first sand member is a tow meter thin sand bed, and the second is about 10 meter and the third is about 22.5 meter[4]. This study is the first reservoir characterization based on 3d seismic survey applied to this field. we will search for a characterization of interest which similar or better to that found in KT_1 in the surveyed area in the targeted formation by producing a porosity cube with aid of well logs and use of Genetic inversion method is an attribute based inversion where attribute seismic cube related to log properties has been calculated after tying the well data to seismic. An effective porosity calculated from well log data correlated with inverted Acoustic impedance cube producing the porosity cube.

Figure (1-1): Location of area of study with surrounding oil field After [1].The area of 3-d Survey about 8886.16 Km2 and the coordinates in UTM.

2. Literature Survey

Artificial neural network becoming an important tool for reservoir characterization, Hampson et al.(2001)[3] pioneered neural network application for reservoir characterization by describe a new method for predicting well-log properties from seismic data, by deriving a linear or noon linear multi attribute transform, between a subset of the attributes and the target log values. Two types of neural networks used: the multilayer feed forward network (MLFN) and the probabilistic neural network (PNN) due to its mathematical simplicity. In (2009) Veeken et al. [8] suggest a new method for seismic inversion for post stack seismic data and reservoir modelling by using a noon linear multi trace seismic inversion algorithm, this method was reliable more robust, fast, user friendly and cost effective. It uses a combination of neural network ANN and genetic algorithm. This method can be used for any log data but relationship between logs and seismic should be identified. Jun 2009 Ampilov et al. and others [11] used the Simi automatic genetic inversion technic for reservoir property prediction in the Shtokman gas/condensate field by inverting 3D post-stack seismic cube to AI cube with relevant logs, curve fitting and Gaussian simulation techniques are used to populate the property model with reservoir parameters and compared with conventional geologic model, genetic inversion earth model was higher in resolution and considered of better quality than the existing conventional model and it can be used in the further development planning of the field. In (2010) Pavlova and Reid [9], used genetic inversion to predict porosity by using 3D seismic and logs data to assist in planning for new well location and predict the well productivity in Panax's Limestone Coast Geothermal Project, to developing a geothermal resource in South Australia. In (August 2014) Kovalenko and others proposed new approach for very effective reservoir characterization by predicting dynamic petro physical properties in this case (effective porosity). By comparing core and log data, the relation between effective porosity and acoustic impedance, as the linear relation between seismic and petrophysical properties have defend, and by applying genetic inversion, they create the volume of the property. The result confirmed by seismic attribute analysis [K. V. Kavalenko 2014]. Gorain and Thakur in (2015) [10], developed a workflow for reservoir characterization based on Genetic inversion technic, they calculate a 3D attribute volume of petrophysical properties then utilized it for reservoir classification and finally geostatistical modeling is performed for reservoir modeling. This workflow was effective even with thin bed which not detected by seismic attribute and effective in determining the reservoir geometry and quality and can help in planning for future drilling locations. In (2016) Ouadfeul and Aliouane invert total organic carbon (TOC) by genetic inversion in shale reservoir, acoustic impedance (AI) from sonic and density logs trained with seismic cube and inverted AI cube resulted, cross plot of the acoustic impedance versus the TOC used to provide a linear relationship between them, an inverted TOC cube from the inverted cube of the acoustic impedance obtained. The result shows the ability of genetic inversion to enhance the reservoir characterization in shale-gas reservoir.

3. Methodology

3.1 Data Preparation

OEC undertaken petrophysical evaluation on wireline logs from well KT_1 (4410m) and KT_2 (3874m). Porosity has been calculated from sonic and density logs, Volume of shale calculated from GR logs to correct porosity to effective porosity. Seismic cube is considered to be preserved attribute in processing stage. Relative acoustic impedance cube has been calculated to be the input of inversion. A good relation between inverted AI logs and effective porosity correlation allow the inversion between the inverted AI volume and effective porosity.

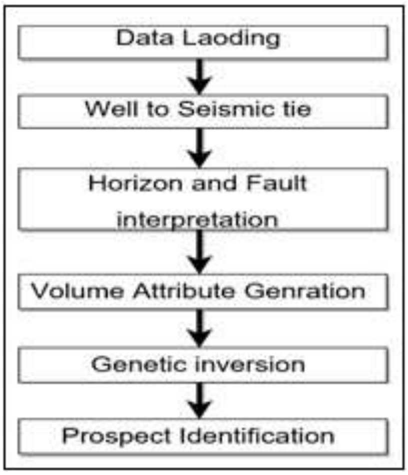

Figure 1: Workflow of reservoir characterization and prospect identification

3.2 Horizon Piking & Fault Interpretation

A TWT map generated along the picked horizon (figure 4) with contour interval 10ms and ranging between (2110 ms to 3320 ms) showing a structure plunging NW-SE and fault parallel to it traverse the foot of the limp. The structure and the fault are irregular shape and the structure shows three small closer the middle which already drilled by KT_1 while KT_2 drilled out of the structure and the other two closer not drilled and showing a good prospect area. The structure with surrounding oil field structures like (AL Noor, Dujela, Ammara) is in the same direction and same basin. The map also shows that the limp is steeper in the NE. A noise structure appears in the NW which need more investigation. The mid closer which penetrated by KT_1 Dimensions (10216m X 10829m), the SE closer (1100m X 1000m), the NW closer (4000m X 120m). Figure 5 a 3d seismic with picked horizon shows the structure and the fault and its orientation. Should be mentioned that all three closers are surrounded by one big closer.

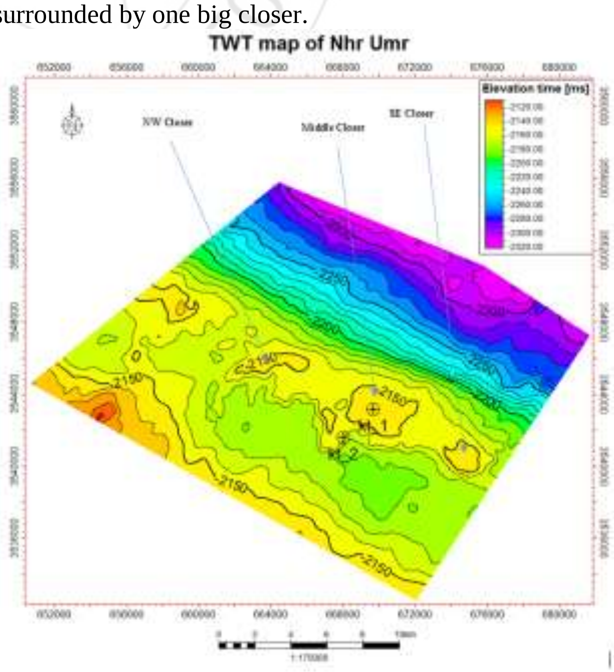

Figure 4: A TWT MAP shows the structure of kumait and the tow drilled well

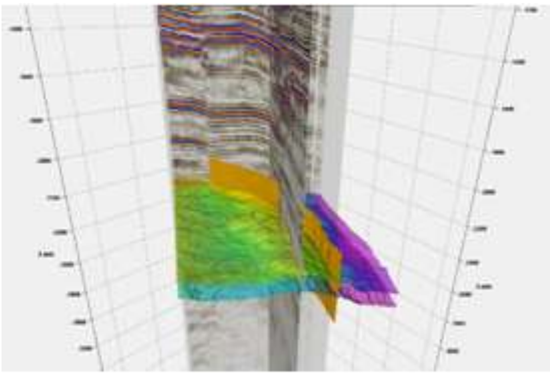

Figure 5: 3D view illustrate the structure and the fault intersect it.

3.3 Genetic inversion (GI)

GI is an approach to inversion and estimating rock property far from wells location, it's a combination from neural network and genetic algorithm. This method characterized by its fast user friendly and cost effective [8]. This approach is patented by schlumberger and incorporated into from Petrel 2009.1 and later versions. Only seismic data post stack and well logs recorded in control wells needed. Horizon interpretation, fault interpretation, and wavelet extraction are not needed in GI which is deferent then model based inversion [8]. In Genetic inversion the neural network used is a multi-layer characterized by a sigmoid activation function (figure 7), only one hidden layer is used for the genetic inversion module.

$$f(x) = \frac{1}{1+e^{-x}} \quad (5)$$

And an input/hidden-layer relationship:

$$y_{hiddin\ layer} = f\left(\sum_{i=1}^{n-1} y_{input\ ,i} \cdot w_{input\ ,i} + w_{input\ ,n}\right) \quad (6)$$

*w*0, *n* and *w*0, *p*_1 represent the bias of
The input layer and the bias of the hidden layer, respectively.

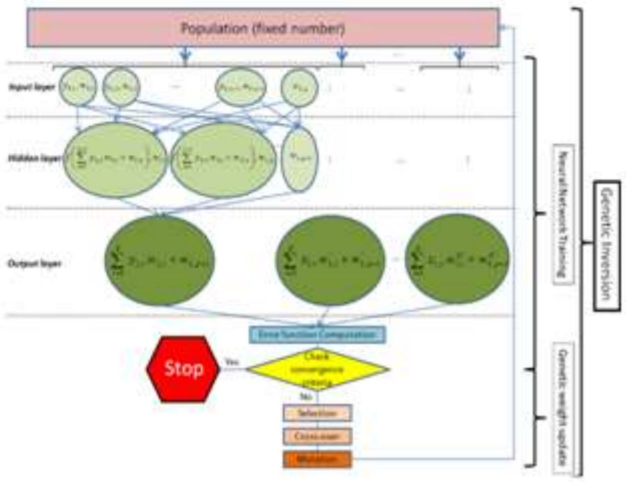

Figure 7: Genetic Inversion procedure behind the user interface [7].

Genetic inversion determine a single nonlinear operator which produce a best fit with well data, this has some similarity with colored inversion which use linear algorithm which compute a series of weight minimized by least square fitting. In the nonlinear, a neural network is trained with logs data, using the selected attributes as input and at least on hidden neuron layer (Figure 8) [8].

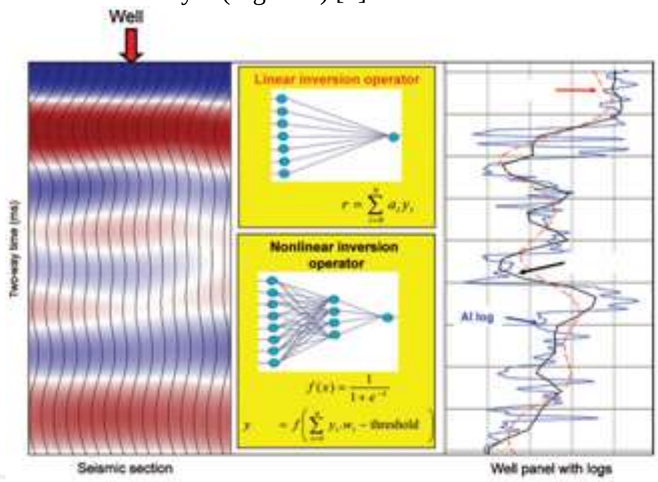

Figure 8: showing the deference between linear and nonlinear operator [8].

Genetic inversion combination from neural network and genetic algorithm so it deals with Weights, every individual input took a randomly generated weight in the first generated set. A computed fitness function by least square error between the measured and predicted log values at the wells, which trained with neural network. A genetic part will take place here in three steps **selection** by selecting the best-fit value for the first generation of individuals are used to create a new generation of individuals . **Cross-over** new generation of weights by taking half of the values selected from first generation and the rest from second generation, giving a newly optimized operator. **Mutation method**, weight factors are randomly changed. Controlled by mutation variability and mutation factor (number of mutation) see figure (9) [8].

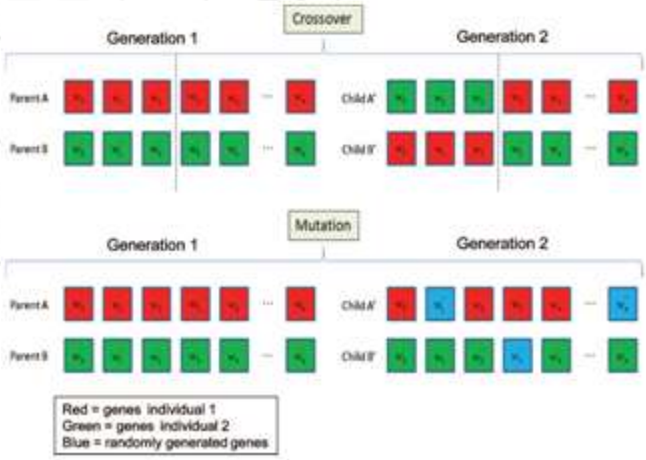

Figure 9: illustration of crossover mutation technic [8].

Normally a 100-ms time window is considered, and nine surrounding traces are taken into account for the computations. The number of surrounding traces can be set as 0–21 in the *x*- and *y*-directions (Xline-Inline). The time window range from 10 to 200 ms. The number of hidden layers in the neural network can be selected from 0 to 10. 0 hidden layer means a linear solution is computed [7]. The top and the bottom of the targeted zone allowed to be set by the program. Computation ofderived Neural Network operator is made step by step each are equal to the seismic sample interval and the process start from "Top surface" down to the "Bottom surface" of the targeted zone [8].

3.4 Application

A novel Simi automatic technic that establish a nonlinear operator for transforming 3d seismic cube into corresponding log property (sonic, GR, AI, porosity...etc.) 3D seismic cube considered to be observed amplitude in processing step this is essential in genetic inversion, a relative acoustic impedance attribute generated from volume attribute using petrel 2015 softwareThis will be trained with AI logs after applying some smoothing to these loge because the logs is much higher in frequency(figure 10), some conditioning to the logs needed like, despike, and smoothing. Because seismic is much lower frequency than log data. We should be careful of not to edit out important features of the log response like (gas-water contact, oil-water contact) [8]. Training the relative acoustic impedance volume with smoothed AI logs an obsolete AI cube will be obtained.

The genetic inversion output correlation between the Smoothed and inverted porosity was calculated at the wells correlation per well is computed by cross plotting the input and the inverted AI that is extracted from the Acoustic impedance cube along the well for every well. The linear regression coefficient is then calculated for the global wells correlation, a good global correlation for the two wells shown in the result from the (figure 11). From input parameter options we can define the maximum number of iterations and the correlation threshold when one of them reached the inversion will stop. Nodes in hidden layer represent the number of neuron in the hidden layer used to compute the inversion operator. The weight decay is the ANN smoother and over fitting prevention parameter. By increasing weight decay correlation could be decrease, the process is repeated until a good match is observed between the actual and the inverted logs. (Figure 11) show the best chosen parameter which gave the optimum result. The reverse relation between AI and porosity (figure 12) when AI increase porosity decrees in reservoir by cross plotting this relation AI log and porosity log we can observe this relation clearly with 0.74 correlation coefficient.

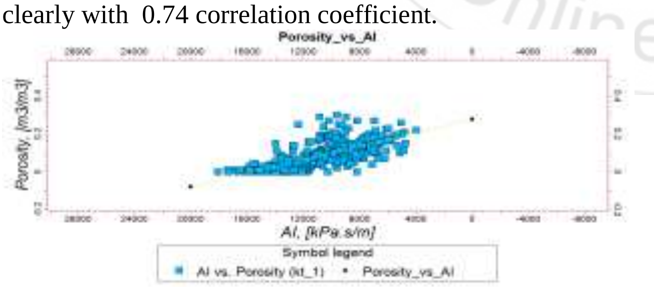

Figure 12: relation between AI and effective porosity log(Y = -1.78039E-5 * X + 0.277397).

The correlation between the AI and Porosity allows the AI inverted cube to be trained with Effective Porosity Logs which calculated as mentioned above for the two wells. This will establish a logical relationship between AI cube and effective porosity (inversion operator) (Figure 12).

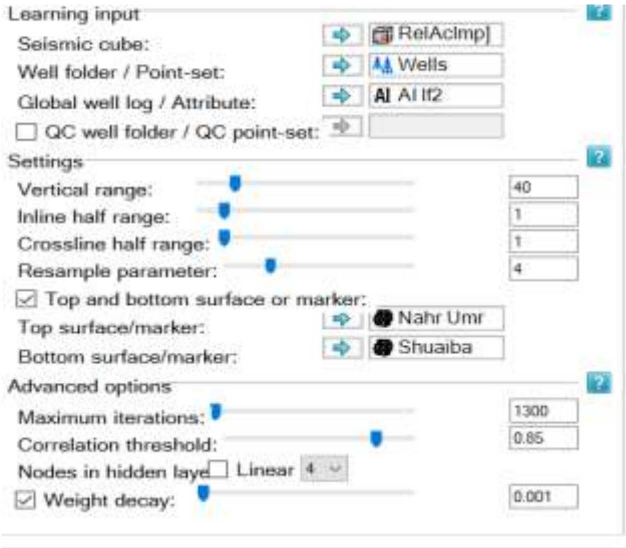

Figure 11: parameters used in the Genetic inversion process.

Genetic Inversion did transform the 3D AI cube into an effective porosity equivalent using the inversion operator. Porosity logs smoothed using median filter taking in to account not to effect a significant feature in logs. The AI and porosity inversions run between two surfaces which represent the top and the bottom of the NahrUmr formation, to constraint the inversion process in the formation of interest.

4. Result and Discussion

This study com to solve the problem of producer and non-producer well and looking for new prospect in Kumait Oil field south Iraq, by studying the characterization of the clastic reservoir (Porosity in this study).Prediction of log property away from well location is the main reason of using seismic inversion, and porosity was always one of its main purpose due to its relation to the accumulation of hydrocarbons. Inverted AI cube by the technic mentioned above and correlation coefficient observed between the input logs and inverted cube in (figure 12) shows a good correlation between the input and output AI logs in the two wells with global correlation about 0.85

AI cube then trained with effective porosity log as we mentioned above porosity cube with a good global correlation about 0.80 resulted between inverted and inputed logs.

- Correlation = 0.8006698
- Learning wells:
- Created predicted log for : kt_1 (Correlation = 0.8060302, Samples = 62)
- Created predicted log for : kt_2 (Correlation = 0.7487203, Samples = 26)

A good matching between the inputted logs and the inverted cube (figure 14) high porosity can be observed near bottom of the formation where the produced sand beds is located.

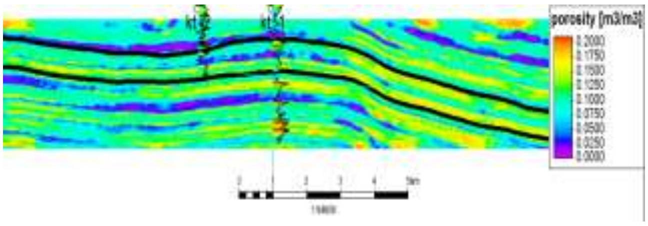

Figure 14: Inverted cube with inputted porosity logs.

Some discrepancy between the wells and the cube in this area may be due to existing of thin sand beds about 2 meter represent the first member and thin shale beds which separates the sand beds making a cap rocks between them, these beds thickness is less than seismic resolution so they cannot be detected by seismic data making this discrepancy between the inputted logs and observed cube. Also due to the smoothing window length it does not detect porosity of thin beds, while in conventional inversion methods the initial model contain a low frequency built by well data, when add it to seismic extend its bandwidth and hence its detection ability, but the seismic is usually not able to represent this part of the data. Porosity map of reservoir pay zone (figure 15) we can observe a good porosity estimated at the reservoir level in anticline area which make it a good reservoir prospected area also the area after fault location dipping area in the NE show a good reservoir porosity much higher velocity values and the existing of fault increase the possibility of exiting of hydrocarbon accumulation. The inversion result indicate changes in porosity latterly and vertically.

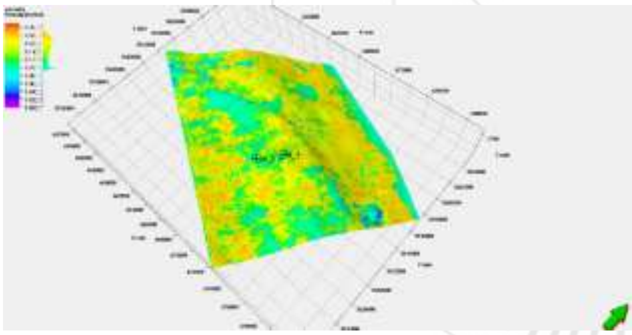

Figure 15: horizon slice at reservoir pay zone

And we can observe the change in porosity in the top of the formation which may be indicate change in facies the porosity in the top of NahrUmr formation increases in the NE direction but decreases in the anticline area due to the carbonate existence (figure 16) .

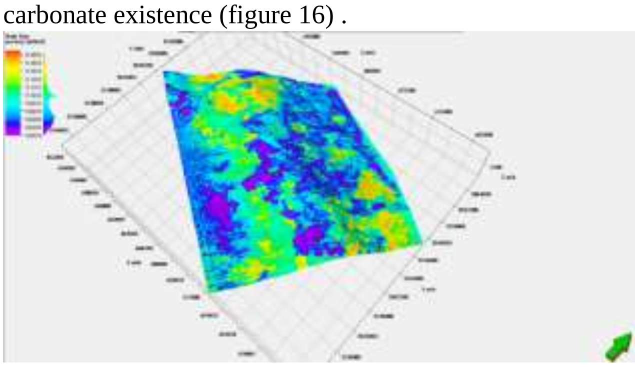

Figure 16: horizon slice for the top of NahrUmr formation indicate change in porosity laterally.

5. Conclusion

This paper was about studying the reservoir characterization in this case porosity looking for a new prospected area and investigate the reason of noon producing well by applying Genetic inversion. This semi-automatic technic was fast robust and user friendly and need only minimum requirement, no need for wavelet extraction or fault interpretation, an anti-cline structure has been delineated and reservoir characterized very well by AI inversion and porosity cube. A new prospected area identified in the field which may help in suggest new wells to be drilled in the future. The method is very flexible it allow invert of any log property but a linear relation should be verified between the inverted properties and chosen attribute. The resulted effective porosity cube will provide a robust analysis tool for studying the Distribution of effective porosity for reservoir modeling and future planning of production and injection. A care should be taken when smoothing the logs data not to edit important feature in the log by choosing a reasonable window length and it can affect the resolution of the inversion. Anomalous area in AI cube and Effective porosity help in determine the new prospected area which may help in future planning and development of new wells.

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