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Subsurface 3D Prediction Porosity Model from Converted Seismic and Well Data Using Model Based Inversion Technique

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Abstract

Seismic inversion technique is applied to 3D seismic data to predict porosity property for carbonate Yamama Formation (Early Cretaceous) in an area located in southern Iraq. A workflow is designed to guide the manual procedure of inversion process. The inversion use a Model Based Inversion technique to convert 3D seismic data into 3D acoustic impedance depending on low frequency model and well data is the first step in the inversion with statistical control for each inversion stage. Then, training the 3D acoustic impedance volume, seismic data and porosity wells data with multi attribute transforms to find the best statistical attribute that is suitable to invert the point direct measurement of porosity from well to 3D porosity distributed volume. The final subsurface porosity model greatly improves the understanding of the distribution of porosity in the reservoir zones and showing the variations of porosity both vertically and laterally. The success of the prepared workflow encourage the transformation it automatically to run the same workflow faster for the areas that have the same characteristics of carbonate Yamama Formation.

Keywords: Model Based Inversion, porosity prediction, Carbonate Yamama Formation, Subsurface 3D model.

موديل تحت سطحي ثلاثي الابعاد لتخمين المسامية من تحويل البيانات الزلزالية والابار بتقنية المعكوس الزلزالي المعتمد على الموديل

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الخلاصة

تم تنفيذ تقنية المعكوس الزلزالي لبيانات زلزالية ثلاثية الابعاد لتخمين خاصية المسامية لتكوين اليمامة الكاربوني (الكريتاسي المبكر) في منطقة تقع جنوب العراق. تم تصميم مخطط ليرشد خطوات العمل والتي نفذت يدويا لمراحل المعالجة. استخدمت تقنية المعكوس الزلزالي المعتمد على الموديل لتحويل البيانات الزلزالية ثلاثية الابعاد الى ممانعة صوتية ثلاثية الابعاد اعتمادا على موديل للترددات الواطئة والمعلومات الزلزالية وهي الخطوة الاولى في المعالجة مع سيطرة احصائية لكل مرحلة. ثم تهيئة الممانعة الصوتية ثلاثية الابعاد والبيانات الزلزالية الثلاثية الابعاد وبيانات المسامية المباشره من الابار مع تحويلات السمات المتعدد لايجاد افضل السمات المحسوبة احصائيا والملائمة للتحويل الى مجسم توزيع المسامية ثلاثي الابعاد. تم الحصول على الموديل تحت السطحي النهائي في نطاق المستودع لتوزيع وتغير المسامية جانبيا وعموديا جيد وبشكل كبير. ان نجاح مخطط العمل المعد والمنفذ يدويا يشجع على تحويله الى معالجة الية لتنفيذ نفس المخطط بصورة اسرع للمناطق التي تحوي نفس الخصائص لتكوين اليمامة الكاربوني.

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Introduction

Seismic exploration is the use of seismic techniques to map subsurface geologic structure and stratigraphic features [1] and 3D seismic measurements have come as an essential element for reservoir description [2]. The reflection of seismic waves from subsurface layers illuminate potential hydrocarbon accumulations, as waves reflect and their amplitudes change reveals important information about the underlying materials. Seismic amplitude inversion uses reflection amplitudes, calibrated with well data, to extract details that can be correlated with porosity, lithology, fluid saturation and geomechanical parameters [3]. The seismic method measures only four fundamental rock-physics properties; that is P-wave velocity, S-wave velocity, density, and anisotropy. Only the first three properties are measured with the accuracy required for inversion. Inverting seismic data to other rock properties implicitly assumes a relationship between the property of one or more of these fundamental properties. All types of inversion require some form of constraint and need to be calibrated by tying the result to real or simulated well data [4]. The integration of well-log and seismic data has been a consistent aim of geoscientists. This has become increasingly important (and successful) in recent years because of the shift from exploration to development of existing fields with large numbers of wells penetrating them. One type of integration is forward modeling of synthetic seismic data from logs and the second is inverse modeling of logs from seismic data this is called seismic inversion. So, inversion is the process of extracting from seismic data, the underlying geology which gave rise to that seismic information [5]. Berge, et al. [4] defined the inversion as an attempt to predict rock properties (porosity, thickness, fluid content, hydrocarbon saturation, etc.) from seismic data. Other definition of seismic inversion is presented by [6] as the technique for creating sub-surface geological model using the seismic data as input and well data as controls. Kemper, 2010, [7] defined seismic inversion as the process of converting seismic reflectivity data to rock property information ranging from Acoustic Impedance (A.I.) to petrophysical properties such as porosity, volume of shale, and water saturation.

The objective of the current paper is to perform inversion over 3D seismic volume to predict the porosity property for a selected carbonate formation located in an area in southern part of Iraq through utilizing CGG program.

Methodology

The inversion workflow includes using STRATA module for converting 3D seismic data of this formation into 3D A.I. model by using a suite of different logs from five wells (A, B, C, D and E) in the surveyed area. The suites of logs are including density, sonic P-wave, porosity, and well velocity survey (Check Shot). Well logs data are in depth domain while seismic data are in time domain. Synthetic seismogram comes to resolve this problem by unifying depth and time as one parameter. Target carbonate horizons are defined from synthetic and picked through all volume seismic data to build an initial model for inversion, next step run inversion analysis to perform inversion over volume and invert seismic data into 3D A.I. volume. Finally, by using EMERGE module train the inverted 3D A.I. with 3D seismic data and well porosity log to predict porosity property over volume.

STRATA is a module used to perform both post-stack and pre-stack inversion. In the classic post-stack domain, STRATA analyzes post-stack seismic volumes to produce an acoustic impedance volume (A.I.). In the pre-stack domain, STRATA analyzes angle gathers or angle stacks to produce volumes of acoustic impedance, shear impedance and density.

EMERGE is a module uses a combination of multiple seismic attributes to predict some reservoir parameter of interest that can predict rock property volumes using both well logs and attributes from seismic data, The idea of using multiple seismic attributes to predict log properties was first proposed by [8]. The predicted properties can be essentially any log types available, such as porosity, velocity, density, and shale and water saturation. Using multi-linear regression or neural network analysis, EMERGE trains itself at the well locations to learn the optimum transform that relates the logs and seismic data. It then applies that transform to derive a volume of the log property from the seismic volume(s). Figures-1 and 2 summarize workflows for the steps that have been dependant in this research and the following gives an explanation of some details for these steps with its theoretical background.

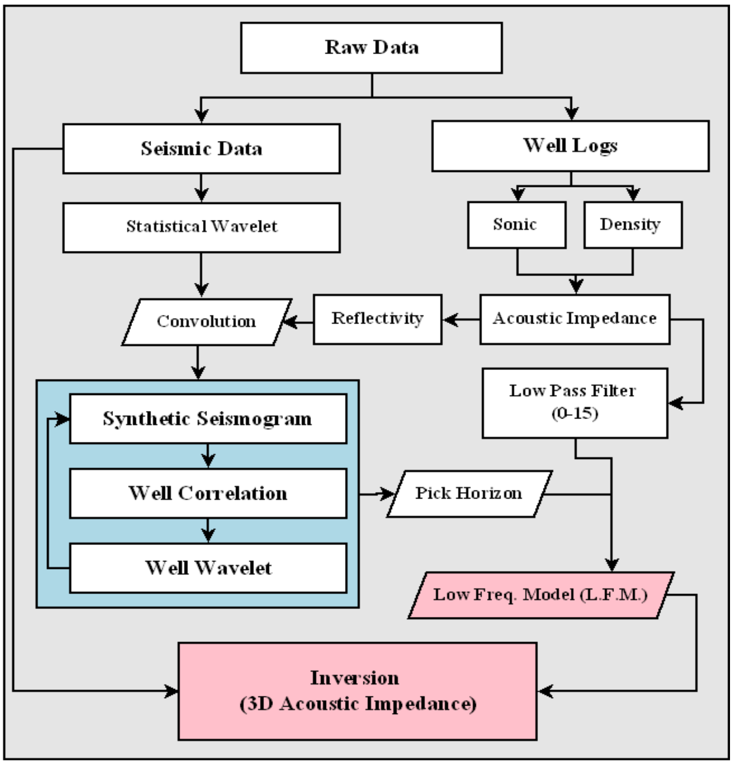

Figure 1- Summarize the workflows for steps utilized by using CGG Strata program to convert 3D seismic data to 3D A.I. model and depending on well logs data.

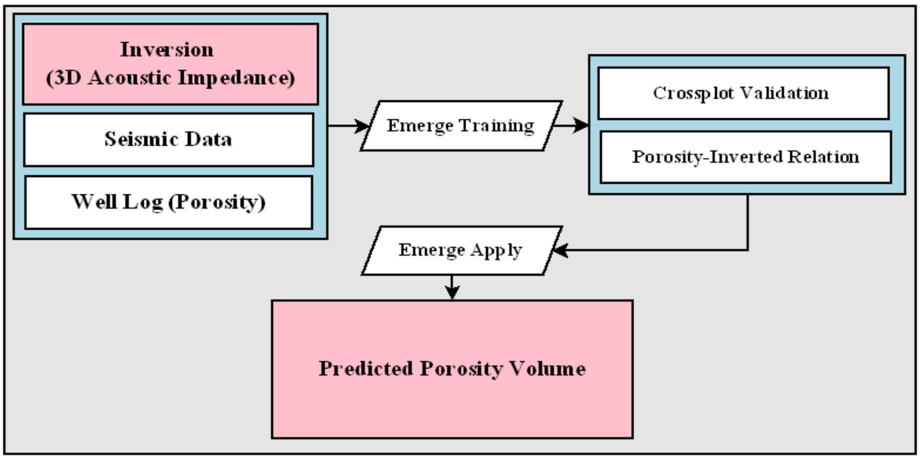

Figure 2- Summarize the workflows for steps utilized by using CGG Emerge program to convert 3D A.I data to 3D predicted porosity volume depending on seismic data with well log porosity data.

Seismic Wavelet:

Wavelet can be defined as the link between seismic and impedance cube and used to create synthytic seismogram. The seismic traces (in the stacked seismic section) can be modelled as the convolution of the earth's reflectivity and a band limited seismic wavelet which can be written as:

$$S = w * r \tag{1}$$

Where: S is the seismic trace, w is the seismic wavelet and r is the reflectivity and *denotes convolution.

The reflectivity, is related to the A.I. of the earth by:

$$r_{Pi} = \frac{Z_{Pi+1} - Z_{Pi}}{Z_{Pi+1} + Z_{Pi}} \tag{2}$$

Where:

Pi is the zero-offset of P-wave reflection coefficient at the i*th* interface of a stack of N layers.

$Z_{Pi} = \rho_i \times VP_i$ is the i*th* ρ-impedance of the i*th* layer., where ρ is density, VP is P-wave velocity [9].

Lindseth, 1979, **[**10**]** showed that if we assume that the recorded seismic signal is given in equation (2), we can invert this equation to recover the P-impedance using the recursive inversion equation given by:

$$Z_{Pi+1} = Z_{Pi}\left[\frac{1+r_{Pi}}{1-r_{Pi}}\right] \tag{3}$$

By applying equation (3) to a seismic trace we can effectively transform, or invert, the seismic reflection data to P-impedanc (Inverse Model). The low frequency component of the reflectivity is removed by the effect of band limited wavelet, i.e. it cannot be recovered by the recursive inversion procedure of equation (3). After proper processing and scaling of the seismic data, the low frequency component of the reflectivity should be recoverd and this done simply in an intuitive approach by extracting this component from well log data and add it back to the seismic. This recent approach of inversion is called Model-Based Inversion [8]. In Model-Based Inversion (M.B.I.), the inversion start with a low frequency model of the P-impedance and then training this model until obtain a good fit between the seismic data and synthetic trace computed by applying equations (1) and (2). Both recursive and model-based inversion use the assumption that extracted a good estimate of the seismic wavelet [11]. A wavelet amplitude spectrum could be extracted by analyzing the autocorrelation of a set of traces over a selected time window [12].

Two basic methods for extracting the wavelet could be proceeded within CGG-STRATA module, That is:

- The first is statistical: by using seismic data alone to extract the wavelet and estimate the amplitude spectrum from seismic data, the phase of the wavelet cannot be determined from the data itself, so the phase must supply by user. Zero phase is the default and is commonly used for wavelets for log correlation [13]. The extracted wavelet from the stacked seismic data is shown in Figure-3, where the time domain response of the wavelet is shown on the top, and its frequency domain response on the below.
- The second method is by using the well data (sonic and density log) to give a good estimate of both amplitude and phase spectra of the wavelet, but this method should be used after correlated wells and determine the proper depth-time relationship [13] Figure-4. the methods applaied in this research during create synthetic seismogram process.

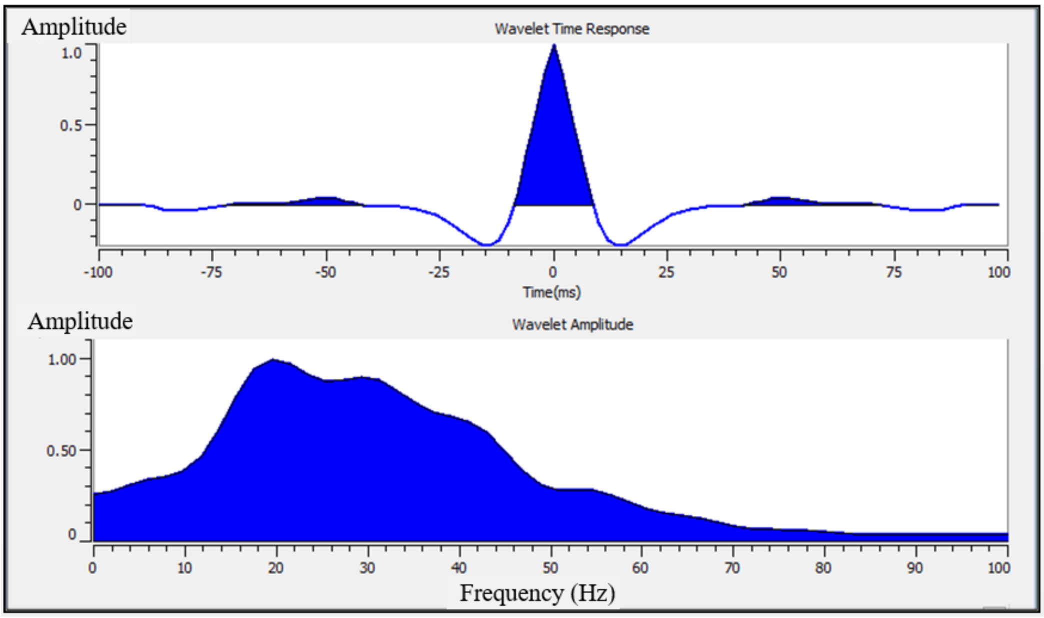

Figure 3- Extracted wavelet statistically from input seismic data.

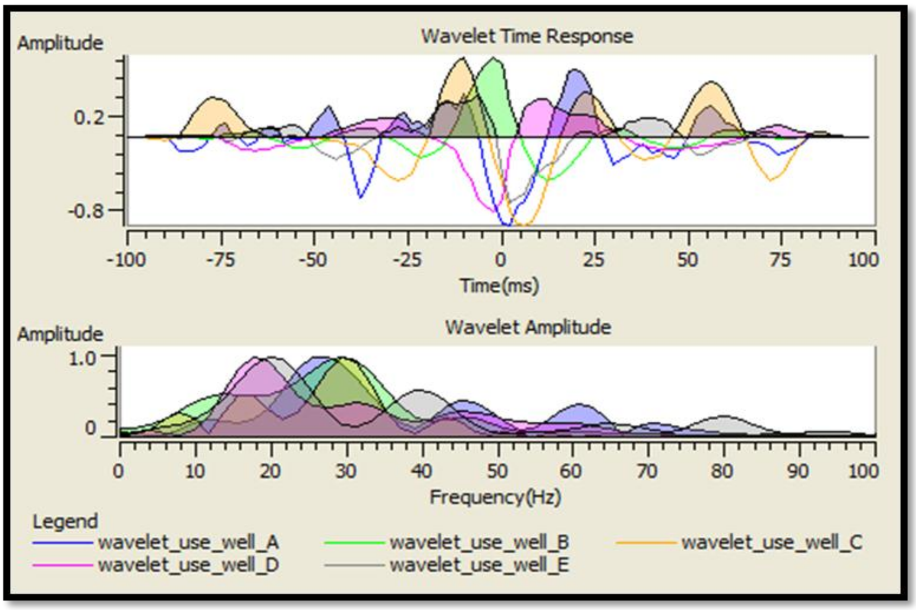

Figure 4- Wavelet extracted for all wells with their phases in the study area.

Synthetic seismogram:

Synthetic seismogram is a plot compare between synthetic trace and composite trace (original seismic data collected near the well location), synthetic trace created by convolution process between reflectivity calculated from well data and statistical extracted wavelet. The primary well data required to generate a synthetic trace are sonic log (inverse of the sonic log is the acoustic velocity), density log and check shots data which are also very important. Sonic log is the principle source of well velocity data. It provides direct information about the borehole and the rocks penetrated by the drill bit. The sonic log is a measure of the time necessary for a sound wave to traverse one unit of the earth along the well bore, usually labeled 'DT' and the reciprocal of DT is the velocity (in m/s). The unit for sonic log is microseconds per foot or microseconds per meter [14]. The aim is to match the measurements made through well logs (in depth domain) to the seismic data (in the time domain). Thus, check shot correction had been applied with STRATA-CGG program to make appropriate well-seismic tie for all wells in the study area. Later on, the corrected synthetic seismogram is correlated with the seismic volume in wells location to optimize depth-to-time conversion Figure-5.

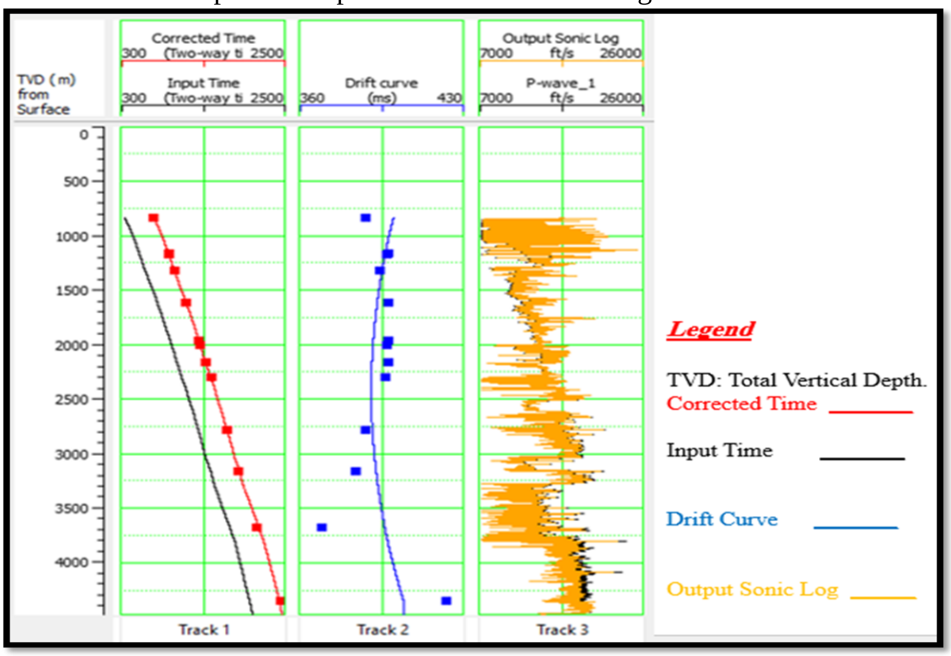

Figure 5- Check shot correction is applied using STRATA-CGG program.

The procedure of creating synthetic is by multiplying the velocity (time-depth relation resulted from check shot correction) and density data to produce the A.I. data for each reflecting interface in the subsurface and according to the following equations:

$$Z_{Pi}=\rho_i \times VP_i \quad (4)$$

Where: Z_{Pi} is acoustic impedance, ρ_i is density and VP_i is velocity from sonic log.

Reflection coefficient: The reflection coefficient is simply the difference in A.I. between stratigraphic layers divided by their sum (equation 2). After that, computed reflection coefficient is convolved with the statistical wavelet to perform a well-to-seismic tie and time shift between synthetic and composite trace. Then, after stretch and squeeze for the synthetic trace a correlation is made for wavelet extracted from well to give a good estimate of both amplitude and phase spectra of the wavelet and Maximum Correlation (M.C.). Group Wavelet (average wavelet for all wells) was used for creating the synthetic seismogram with STRATA-CGG program which give M.C. 0.72 Figure-6.

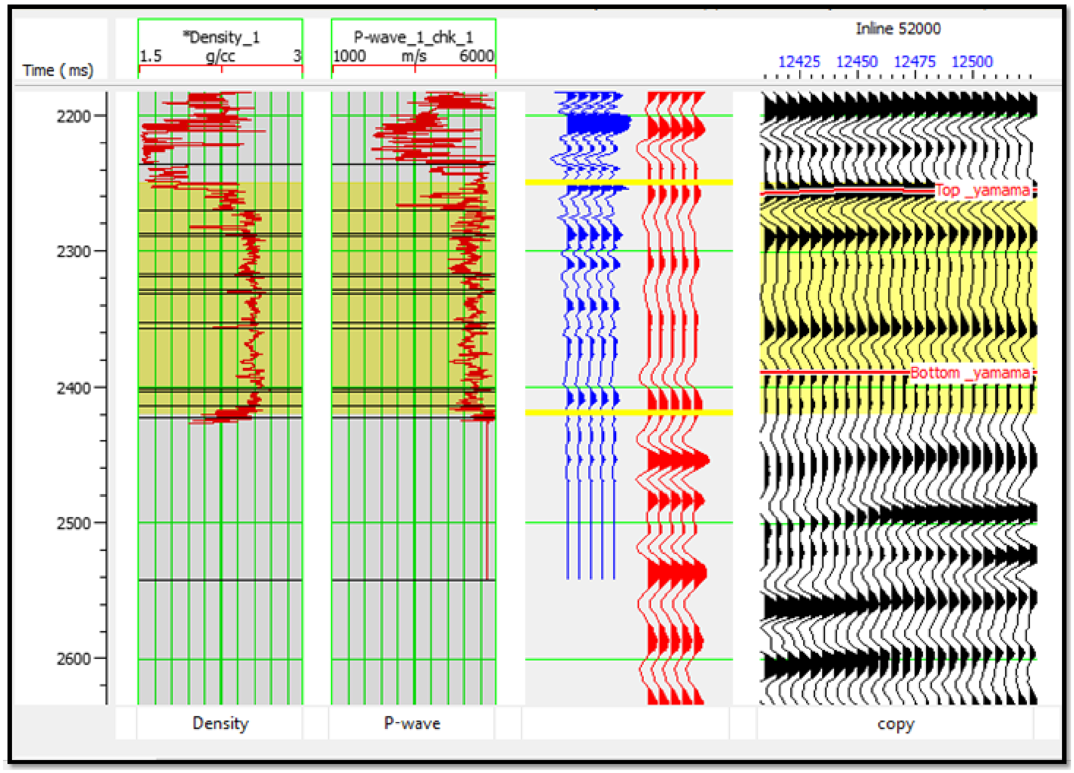

Figure 6- Synthetic seismogram shows correlation between composite trace with red color and synthetic trace with blue color using group wavelet (Corr. Coef. is 0.717 for highlighted area).

The target horizon and interpretation – STRATA module:

The inversion process is aimed to predict the porosity property of Yamama Formation in an area located in southern Iraq. Yamama Formation is a complex carbonate lithology with highly variable porosity of Cretaceous age. Five wells is chosen (named A to E) for accurate well-to-seismic tie, the top and bottom of Yamama Formation are picked in the 3D seismic data for structural mapping Figure-7. The seismic data are then inverted to obtain acoustic impedance (A.I.) using constrained inversion algorithm (M.B.I.) to improve the vertical resolution and the prediction of lateral variations in reservoir quality.

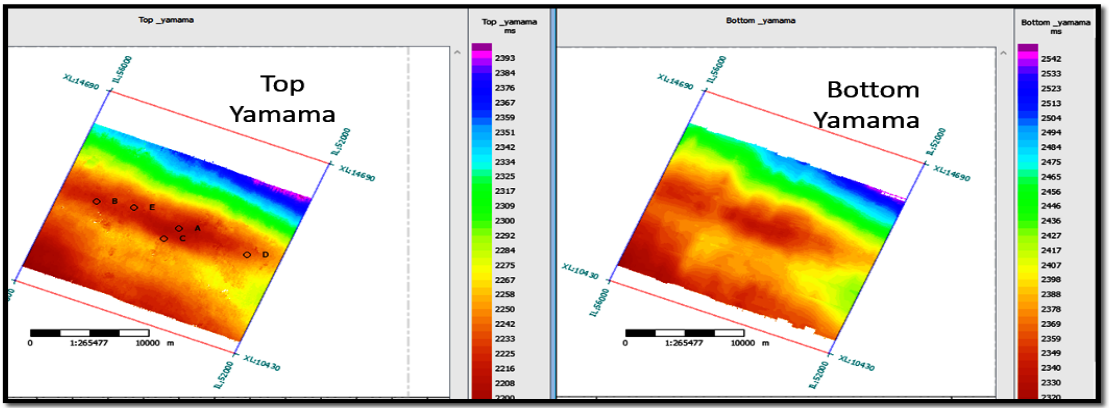

Figure 7- Picked horizon, the left is top Yamama Formation time ranges between (2200 msec with red color and 2390 msec with violet color) and the right is bottom of Yamama Formation time ranges between (2320 msec with red color and 2540 msec with violet color). Map scale: 1:265477

The porosity distribution of the reservoirs is estimated using inverted data of (A.I.). It will be start with building Low Frequency Model (LFM) (Initial Model). The M.B.I. schemes use well logs and picked horizon to construct the LFM and for account the missing low frequencies in the recorded seismic data under the constraints of the geological model and seismic horizons [15,16]. So that, the result with more low frequency information can lead the inversion to be directed by the seismic as opposed to single point location of well logs [15]. The missing frequency bands in recorded seismic data cause problems in the reconstruction of A.I. [17]. When the model is not filled with frequencies that are missing from the low end of the seismic bandwidth, the inversion result becomes driven more by the wells and less by the seismic [18 in 15]. For that, low frequency range between (0 -15 Hz) is added in building the initial model depending on extracted amplitude spectrum from the whole 3D seismic volume Figure-8. The LFM for M.B.I. is formed by blocking an impedance log from well Figure-9.

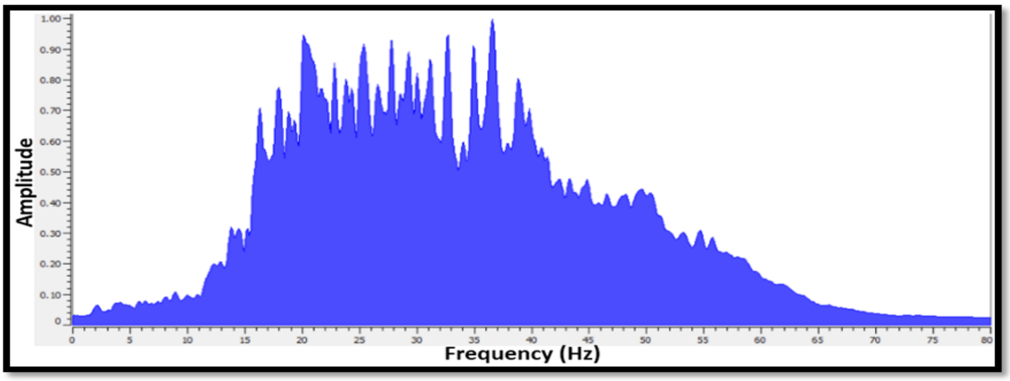

Figure 8- Amplitude spectrum of recorded seismic data, frequency range (0 -80).

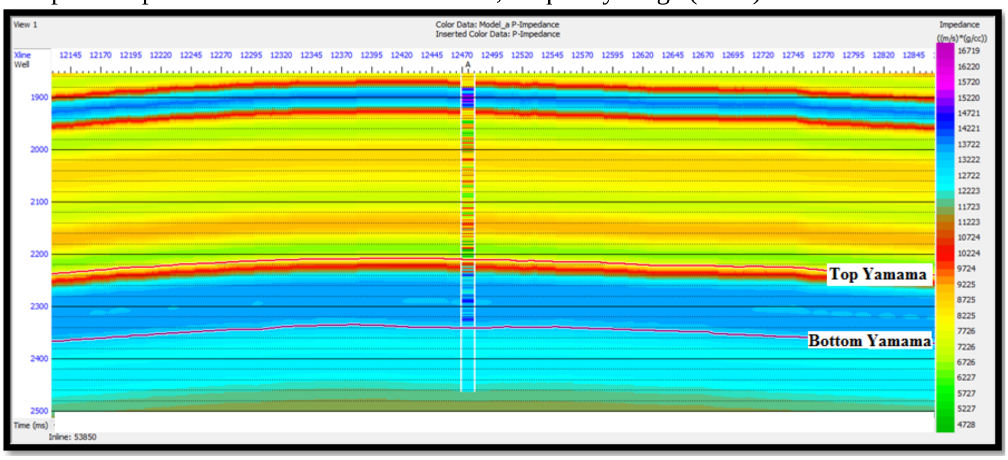

Figure 9- Initial Model used in inversion. The figure shows location of top and bottom of Yamama Formation Green color represents low Acoustic Impedance and violet high Acoustic Impedance in the color scale. Yamama Formation has an impedance values within range between (8188 and 13180).

Inversion analysis:

The inversion analysis tool shows the results of inverted traces at each well location, overlain on top of the original impedance logs. It is also shows the synthetic traces that result from the inverted data and compares them to the input seismic volume. This allows for fast and exact calibration between inversion results with well logs, allowing quality control and parameter refinement to be carried out interactively at the well locations before inversion of the full volume [13].

Figure-10a shows the inversion analysis window to well A. The left hand represents A.I. (original in blue color, low frequency in black color and inverted in red color). It shows the wavelet that has been used in the convolution. In the middle are the synthetic traces (with total M.C. 0.991 after using GROUP WAVELET, Figure-10b for all wells) in red color and original seismic traces in black color. In the right is the picked horizon and the difference Error (=0.068) between synthetic and seismic trace. Another window of the inversion analysis is shown in Figure-11 that represents the crossplot between original A.I. and inverted A.I. with M.C. 0.76.

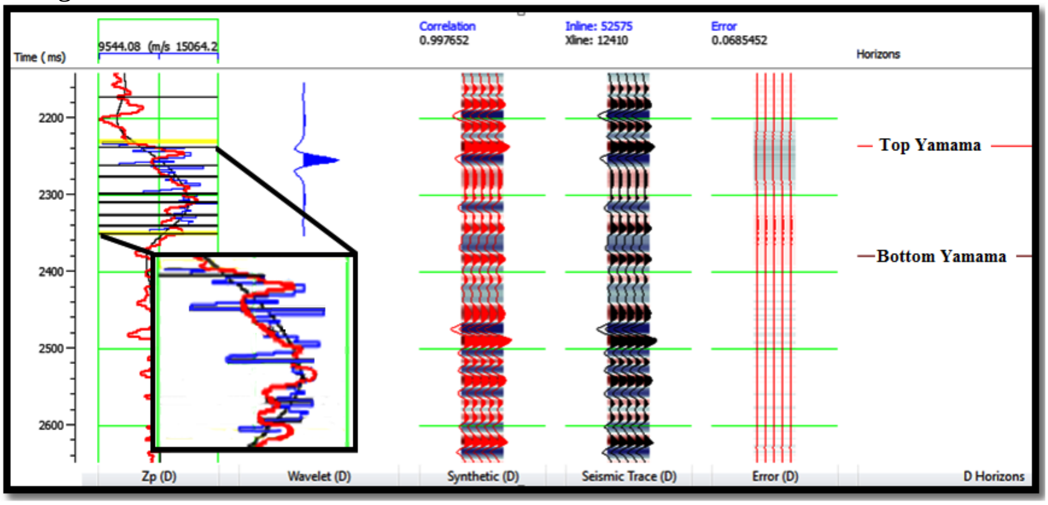

Figure 10a- The inversion analysis window for well A.

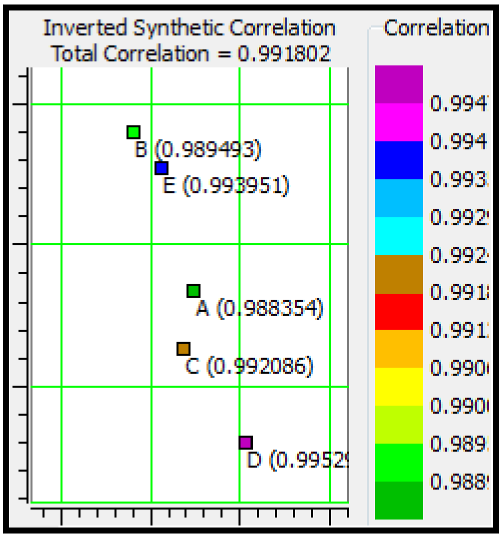

Figure 10b- Base map show the best correlation between original and inverted A.I. at each well location after using group wavelet in inversion analysis.

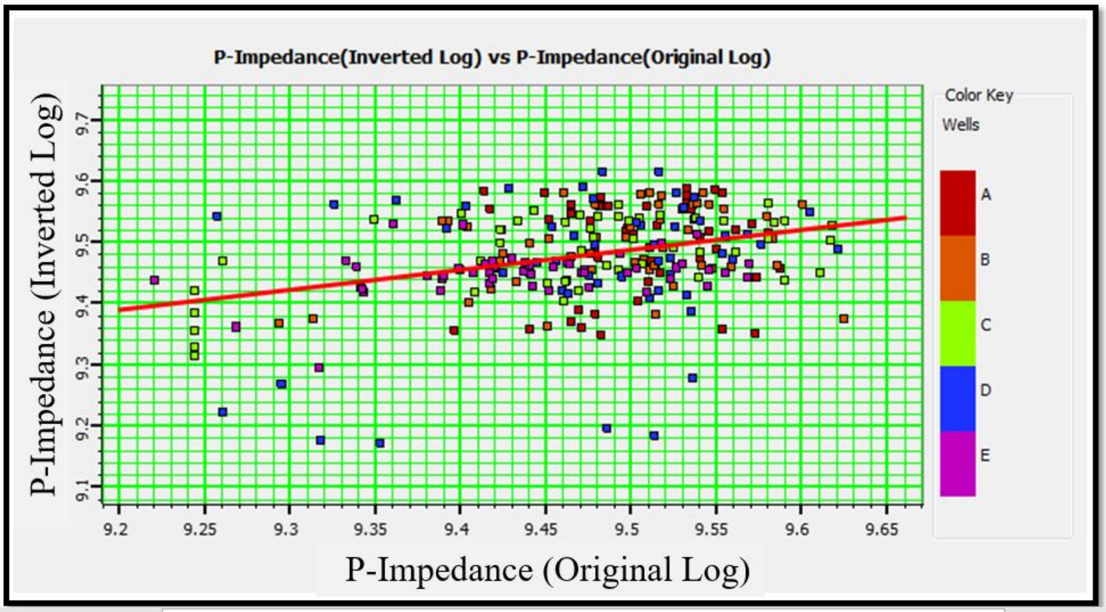

Figure 11-The crossplot between original A.I. calculated by equation (4) from well data and inverted A.I. calculated by equation (2) from seismic data (M. C. = 0.76). Data points for each well are shown in one color.

Final step of M.B.I. is running inversion process for the whole 3D seismic data and the result is 3D A.I. data. Figure-12 exhibit impedance slice extracted within 3D A.I. guided by picked horizon (top Yamama Formation).

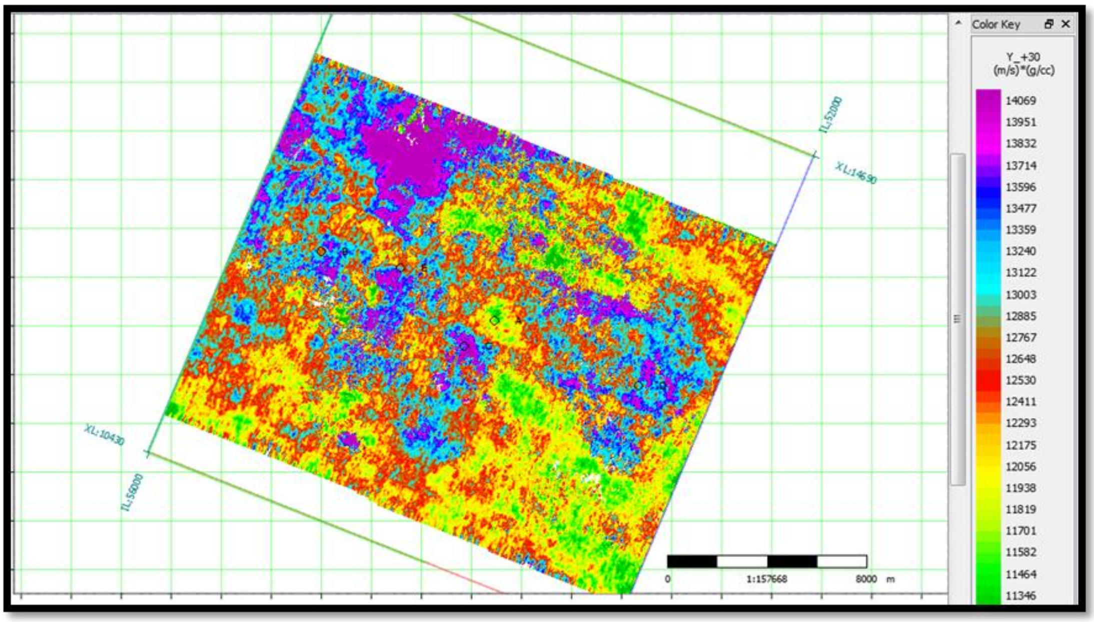

Figure 12- M.B.I. inverted (impedance) slice extracted from inverted data within Yamama Formation (30 msec below top Yamama Formation) green color represents low Acoustic Impedance and violet high Acoustic Impedance in the color scale.

There are two important approaches for checking an inversion results. These are impedance prediction at wells and synthetic–seismic error plots. If the initial model is created using the well as input, then the match is always likely to be good. A better test is to use a 'blind' well, not incorporated in the M.B.I. (Quality Control QC well). This is sometimes referred to as 'cross validation' [19]. The two approaches are used in this research. The first is the synthetic–seismic error plots with least Error (0.06) and M.C. 0.997 (Figure-10a) and the second use well C as blind well when inversion process is applied, Figure (13) shows an example of a blind well test with M.C. 0.685.

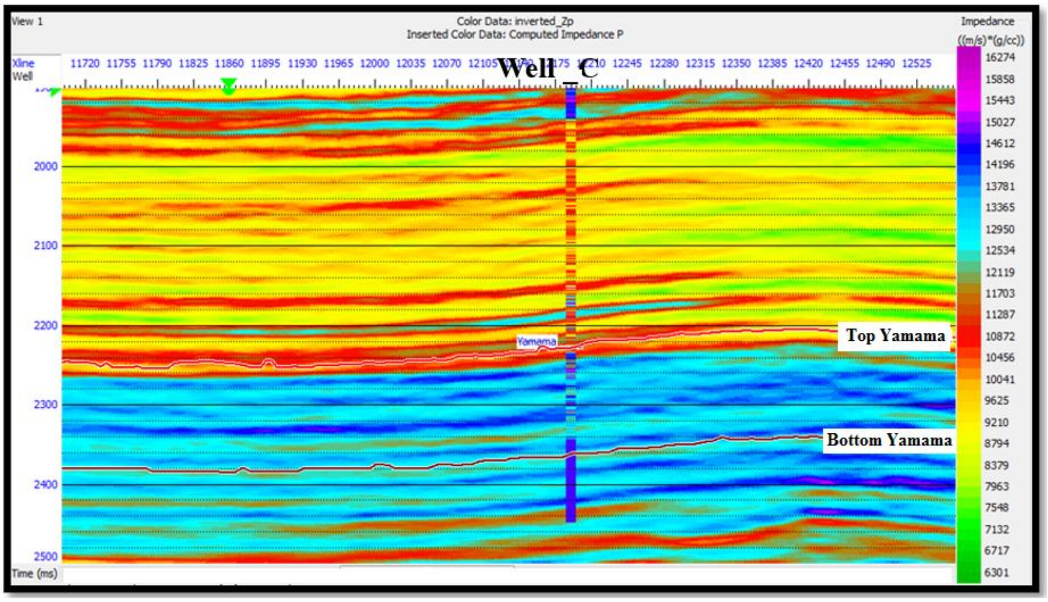

Figure 13- Well C as a blind well to check an inversion results. The M.C. is 0.685.

Predicted porosity property - EMERGE module:

In seismic reservoir characterization, porosity is the main property which controlled hydrocarbon accumulation. Actually this property cannot be measured directly away from the well point. Therefore, seismic inversion is the best tool to predict this property and others such as lithology, volume of shale and (water, gas and oil) saturation with best distribution and create subsurface 3D model for each depending on seismic and well data.

In this research 3D model of porosity is created depending on the information mentioned above (see Figures-1 and 2). EMERGE module is applied using the inverted 3D A.I. data as external attribute and compare it with 3D seismic and well data (porosity log) to create relationship in well location Figure-14 through using internal algorithm provided in this application (No. of the internal algorithm is 28). These algorithms are representing different types of attributes. This step in the EMERGE is named training and sometimes called multiattribute transforms. The result of the training is a crossplot validation error graph which estimate the best algorithm (statistically best fit attributes) correlated to log porosity in the wells location and used to predicting of porosity over 3D A.I. data Figure-15. Finally and depending on the relation with well location, a conversion for all data is applied to produce a 3D porosity data. Porosity slice guided by picked horizon extracted along the 3D porosity which represents the final model and greatly improves the understanding of the distribution of porosity in the reservoir zones showing variations in porosity both vertically and laterally Figure-16.

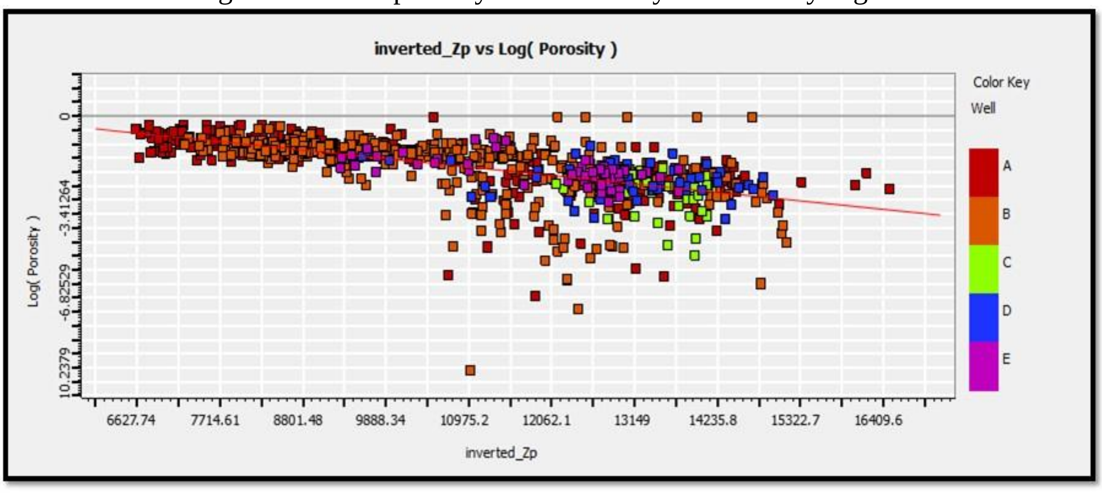

Figure 14-Crossplot shows a relation between inverted data and porosity from well log with M.C. is 0.78. The figure shows a good agreement to predict porosity using multi attribute transforms. Data points for each well are shown in one color. At lower porosity the model slightly under predicts the porosities.

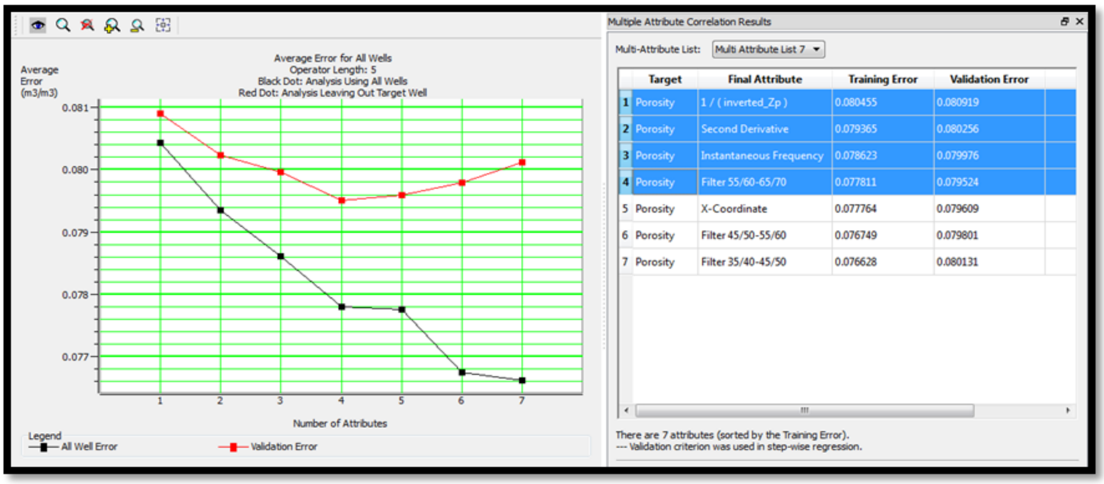

Figure 15- Crossplot validation error, the left shows No. of algorithm in the horizontal axis and Prediction Error in The vertical axis. The lower (black) curve shows the error calculated using the Training Data and the upper (red) curve shows the error calculated using the validation Data. This meaning, only the first four algorithms will be used for porosity prediction. The right used algorithm (Inverted A.I., Second Derivative, Instantaneous Frequency and Filter 55/60-65/70).

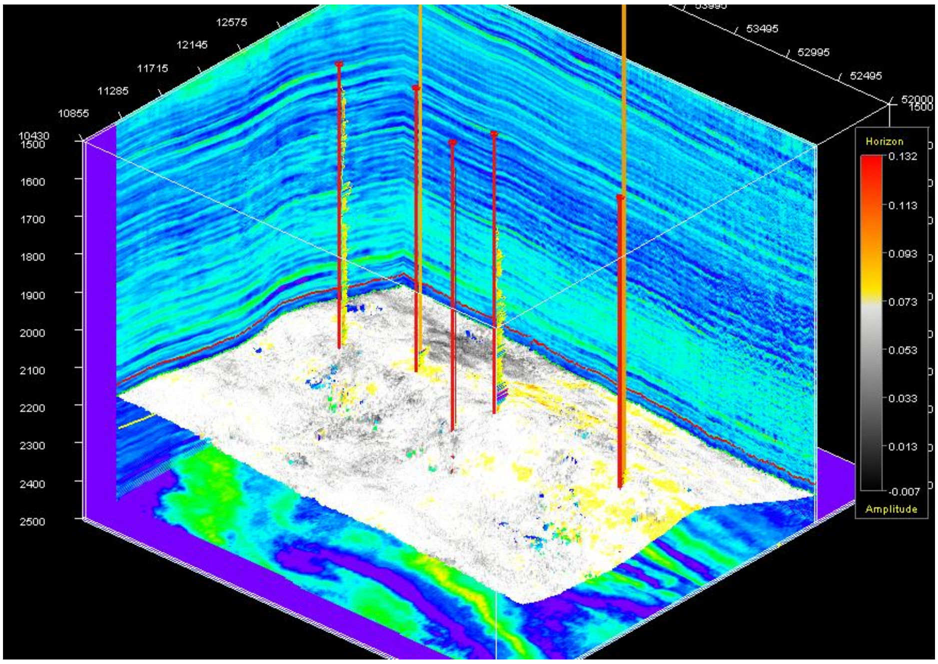

Figure 16- 3D model of porosity extracted along Yamama Formation. Yellow color area shows locations of higher porosity.

Conclusions:

The prediction of porosity property by using seismic inversion method is needed for intensive and judicious systematic work. The results is depending on the suitable designed workflow for wavelet extraction and controled by statistical assessment in each steps of the inversion workflow. Crossplot of each step should be used to check its success. Otherwise, the step should be repeated to enhance the statistical values of the results. The enhanced repetition in the steps of the workflow and the inversion results showed that, wavelet extracted from well data give good correlation in creating synthetic seismogram than statistical and group wavelet used in inversion analysis that gives the best correlation. It is found that, low frequency between (0 to 15 Hz) when added to seismic data in the creation of initial model stage is leading to increase the seismic data control during the inversion process. The inversion result at well C is not bad when it is used as blind well. Porosity around well A, B, D and E gives good discrimination than well C. Locations of low A.I. in all wells within Yamama Formation show high porosity in the inversion result and that support the determination of the predicted porosity for the remaining area of the formation depending on seismic inversion. The execution of each step in the workflow is done manualy. The success of the workflow guide to convert it to automatic design to be run more fast and to be applied directly for the same formation in anothor different area in the region that has same depositional environment for Yamama Formation

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