Facies probability application for gas reservoir characterization

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Abstract. Reservoir characterization through seismic inversion is the principle method in hydrocarbon exploration. Facies probability is an advance method of reservoir characterization which integrates model-based seismic inversion and facies classification to construct a better reservoir modelling. The reservoir modelling is produced from four main steps. First is crossplot analysis to define the relation between acoustic parameter and petrophysics parameter. Second, model-based seismic inversion to produce acoustic impedance volume from seismic data. Third, facies classification which is defined from porosity effective, shale volume and water saturation. Final step is Bayesian Inference Framework to model probability density function (pdf) of each facies. The result of crossplot analysis shows that there is a linear relationship between acoustic impedance and porosity hence the porosity volume can be derived from the model-based inversion result. Facies classification is divided into two categorical zone, pay and non-pay. Pay zone is categorized as a high porosity layer filled with gas. Its parameters fit with Vshale > 0.6, Sw < 0.7 and porosity effective >0.22. Then estimation is run using Bayesian probability into acoustic impedance volume and porosity volume resulting probability volume of each facies.

1. Introduction
Reservoir characterization through seismic inversion is an essential method in hydrocarbon exploration [7]. There are several methods used in analyzing the result of seismic inversion, facies probability is one. Facies probability is a geostatistical analysis method which transform a continuous property of an attribute to discrete property with intention of producing a straightforward subsurface imaging and honor its uncertainty. Uncertainty quantification is important in decision making. The higher probability of the objective the better the decision [3]. Facies probability method is applied to a hydrocarbon field with Gas potential of 6 – 10 TCF. Depositional environment of the field is shallow marine where platform and reef carbonate are deposited. The data base consists of 3D post-stack seismic data and four wells data. 3D seismic data has an approximate area of 162 km\textsuperscript{2} with spacing of 25 m between inline and x line. The well data are supplied with sonic, density, gamma ray, porosity effective, shale volume and water saturation log in each well. The existing log data are comprehensive to perform a fine facies classification.

2. Methodology
The whole process of this study follows a workflow that is illustrated in Figure 1. Full workflow is done by using software Jason Geoscience Workbench. Both seismic and well logs data is acquired by an oil company
back in the 70 s.

There are four main steps to produce probability volume [4]:
1. Crossplot analysis as feasibility study,
2. Model-Based Seismic Inversion,
3. Facies Classification, and
4. Bayesian Inference Framework

Crossplot analysis is performed to assess the viability of the project. The analysis is carried out with plotting acoustic impedance value against porosity effective with water saturation as color scale for all well data. The analysis is performed both in well frequency and seismic frequency (Figure 2) to see its consistency in both domains.

The result of feasibility study shows that there is a linear relationship (red line Figure 2) between porosity effective ($\phi_{ie}$) and acoustic impedance ($AI$) with correlation of 0.82. The relationship is formed according to a linear equation:

$$\phi_{ie} = (-0.000042 \times AI) + 0.057$$  \hspace{1cm} (1)

The linear equation then uses later to perform a conversion from acoustic impedance volume to porosity volume. The analysis shows the AI range of reservoir as well. It ranges from 3000 to 7000 g/cc*m/s. The main method performed in this study is model-based inversion. The inversion utilizes 3D seismic data and logs data from four wells to transform seismic data as lithology boundary to internal absolute acoustic impedance. Low frequency model is built from well log data and horizon constraint then is convolved with wavelet to produce a synthetic volume. The synthetic volume is compared with the actual seismic data then iteratively processed to get the least residual value. The model-based inversion process is illustrated in Figure 3.
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Figure 3. Model-Based Inversion Process

The process is conducted with average well correlation of 0.7 using 100 ms statistical wavelet. Vertical gate of the process is limited by top reservoir (red horizon) to base reservoir (blue horizon) with ± 300 ms above and below. The absolute AI volume could characterize the gas reservoir in range of 3000 – 7000 g/cc*m/s with a bluish color in AI section (Figure 4). Target layer of this study is limited by top reservoir and its base.

Figure 4. Acoustic Impedance Section

The AI volume then transform using linear equation mentioned before to porosity volume in Figure 3. Based on well log data, the porosity of gas reservoir is characterized with value over 0.22 with green to yellow color in porosity effective section (Figure 5).
The third main process is facies classification. Facies are divided into two categorical zone, pay zone and non-pay zone. Pay zone represents the layer contains hydrocarbon and vice versa. Facies classification is analyzed using crossplot of acoustic impedance (AI), porosity effective (phie), water saturation (Sw) and shale volume (Vshale) data from wells (Figure 6).

The analysis shows that the cut-off parameters of pay zones are Vshale > 0.6, Sw < 0.7 and porosity effective...
>0.22, apart from those parameters are non-pay zones. Hereafter, the categorical facies are made based on
the analysis result. Figure 7 is a qc crossplot of AI, Vshale and porosity effective with facies as color code.
The crossplot is made to examine the result of facies classification and it shows that there is a decent
discrepancy of pay zone and non-pay zone.

Figure 7. Crossplot of Pay and Non-Pay Zone

At last, the Bayesian inference framework is performed to integrate facies classification and seismic
inversion results. This step is where all the geostatistical modelling works. Bayesian inference is the process
of deducing properties about a population or probability distribution from data using Bayes’ Theorem [2].
Bayes Theorem allows prior data to calculate the probability. It expresses mathematically as follows,

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

(2)

where \(P(A|B)\) is posterior probability, \(P(A)\) is prior probability, \(P(B|A)\) is likelihood distribution and \(P(B)\)
is normalizing constant. A is a conditional event that links to B while B is an already occur event. \(P(B)\) is a
normalizing constant to meet a condition where the area of Gaussian distribution should be equal to 1. When
Bayes’ Theorem is induced to distribution of data, the equation can be simplified as:

$$P(\Theta|data) \propto P(data|\Theta) \times P(\Theta)$$

(3)

where \(\Theta = \{\mu, \sigma\}\) is set of parameters that have mean and standard deviation in a Gaussian distribution.
Hence, the posterior probability can be derived from multiplying likelihood distribution and prior
distribution. The input of this process is AI volume, porosity volume and facies categorical log from all
wells. AI and porosity are continuous properties. The distribution of continuous properties can be analyzed
using Probability Density Function (PDF) illustrated in Figure 8.
The prior probability mentioned before is calculated from percentage portions of pay zone and non-pay zone in wells. The percentage shows in Figure 9 where pay zone in target interval is 30% while non-pay zone is 70%. Acoustic impedance and porosity data then change to relative frequency histograms of two categorical facies. AI data generate a pay histogram (red) and a non-pay histogram (green), porosity data generate likewise. The two sets of histograms (Figure 10) then use to process PDF fitting. PDF fitting is a qualitative process to model likelihood distribution of the data to predict the magnitude of occurrence in a certain interval. The fitting process is illustrated in Figure 9. Since the process input consists of two continuous properties volume, the 2D PDF of pay and non-pay are produced from the process.
The final PDF parameter is summarized in Table 1. Standard deviation value shows the confidence level of fitting process. Overall, the standard deviation values are ± 16% of the mean value. In addition, the final correlation values of PDF fitting are high. These two factors indicate that PDF fitting result is relevant.

### Table 1. Final PDF Fitting Parameters

| PDF Shape | Mean  | Std Dev | Corr | PDF Shape | Mean  | Std Dev | Corr |
|-----------|-------|---------|------|-----------|-------|---------|------|
| PAY       |       |         |      | NON-PAY   |       |         |      |
| AI        |       |         |      | Normal    |       |         |      |
| Porosity  | 0.32  | 0.05    | 0.77 | Normal    | 0.18  | 0.06    | 0.7  |

#### 3. Results

Facies probability method results the most-probable volume, Pay frequency probability volume, and Non-Pay frequency probability volume. A most probable section in Figure 11 shows that pay zones (red) are concentrated in two height structures which is characterized as reef. Therefore, the gas bearing layer are most likely reef structures.

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\text{Figure 10. PDF Fitting Process} 
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The Pay probability section in Figure 12 is aligned to the most probable section as well. The highest probability of hydrocarbon layer is range of 70 – 80% in reef. The pay frequency volume can be used for further field development. The four wells are located above the eastern structure hence the exploration of new reservoir can be done for the western structure. For further analysis, these results can be utilized to perform risk assessment study and geobody extraction.

**Conclusion**
Facies probability method can provide a straightforward subsurface image of facies delineation. This workflow successfully enhances reservoir modelling images with adding geostatistical modelling to honor the uncertainty of AI distribution. As a result, the method produces a probability volume to ease the risk of error hydrocarbon exploration and/or exploitation.
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