Reservoir characterization using multiattribute analysis in SLS field, Upper Cibulakan Formation, North West Java

Okta Indah Sulistyorini1*, Sigit Sukmono2, Dona Sita Ambarsari2, Normansyah3
1Undergraduate Program of Geophysical Engineering, Institut Teknologi Bandung
2Exploration and Engineering Seismology Research Group, Institut Teknologi Bandung
3Pertamina Hulu Energi, Offshore North West Java

E-mail: oktaindahsulistyorini@gmail.com

Abstract. SLS field is one amongst the biggest in North West Java block and has been operated, exploited since more than 40 years ago. Upper Cibulakan Formation which deposited back in Early to Middle Miocene, has been contributing large number of hydrocarbon production. Upper Cibulakan was formed in shallow marine depositional environment and consists of interbedded sandstone and claystone with carbonate units in some area. Professionals, especially geologists and geophysicists should be able to tackle the challenges encountered in order to perform effective interpretation on existing assets. In this case, the writer found out that Acoustic Impedance interpretation is not appropriate enough to describe the reservoir. In addition, there are several limitations in data availability such as seismic data in post-stack time migration that hold us to perform further interpretation such as AVO or Vp/Vs and also the absence of several logs in the well data. Based on said reasons, the writer applied multiattributes analysis on the available data to predict S-wave log, and generate Mu-Rho volume analysis to support the analysis obtained from acoustic impedance analysis. Merging the two interpretations, the writer concluded a recommendation of prospect area with porosity >20% and Mu-Rho >7.5.

Keywords: seismic, attribute, multiattributes, acoustic impedance, Mu-Rho

1. Introduction

Have been explored and produced for more than half a century, the Offshore North West Java is a mature field lies in the northern shore of West Java (Aveliansyah, 2016). The Upper Cibulakan Formation has been providing up to 85% of oil production in Offshore North West Java Block. The Upper Cibulakan Formation was deposited as interbedding claystone and carbonates (Ponto, 1987). All conventional plays have been drilled and performed in order to make the most of the reservoir’s production. One of the most popular practice is reservoir characterization using seismic analysis.

However at some cases, common seismic analysis such as acoustic impedance yields not enough satisfying interpretation. In addition, limitation in data availability often impede interpreters to work...
on further advanced analysis. Eleven wells and one seismic post-stack time migration volume is used in this study in order to assess which of the SLS field area contains good quality reservoir. In this case of study, acoustic impedance (AI) analysis was applied and the result highlights that the characteristic of Upper Cibulakan Formation porosity still needs supporting analysis that will add the certainty of the reservoir quality. This leads to the idea of comparing between Lambda-Rho and Mu-Rho attribute results. Lambda Rho represents $\lambda$, which is a sensitive fluid indicator meanwhile Mu-Rho represents $\mu$, which reflects the rigidity of the rock matrix (Goodway, 1997). Both of Lambda-Rho and Mu-Rho are derived from S-wave, which unfortunately, missing from ten out of the eleven wells provided.

Table 1. Available logs on each well in SLS field

| No | WELL | CALI | DT | GR | RHOB | Vs | PAPI | Resi | Checkshot |
|----|------|------|----|----|------|----|------|------|-----------|
| 1  | N-1  | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 2  | N-2  | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 3  | N-3  | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 4  | N-4  | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 5  | N-9  | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 6  | N-10 | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 7  | N-11 | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 8  | N-19 | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 9  | NG-1 | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 10 | SM-1 | ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |
| 11 | SNA-1| ✓    | ✓  | ✓  | ✓    | ✓  | ✓    | ✓    | ✓         |

In this manner, we are looking for a cost-effective method to still carry on with the Lambda-Rho and Mu-Rho despite the real geological condition of the field and the limitation of the data provided. One of the possible options is to perform multiattribute analysis. The objective is to derive a multiattribute transform, which is a linear or nonlinear transform between a subset of the attributes and the target log values (Hampson, 2001). The subset of attributes are chosen by stepwise regression, which can be understood as selecting attributes one by one based on the lowest calculated error. The attributes might be computed from internal attribute, or additional external attribute. In short, one point from the predicted log is described as the sum of attributes with different weights working on it.

2. Methodology

This study highlights the utilization of multiattribute analysis to predict S-wave log in order to perform advanced interpretation of the SLS field, Upper Cibulakan Formation. S-wave log will be yielded from multiattribute prediction, and further transformed into Lambda Rho and Mu-Rho logs from deterministic equation. These new logs will be tested by their capacity to separate reservoir parameters before it constructed into volumes. A map constructed from slicing the volume is hoped to shed a new light in describing the target zone with sharper analysis than AI. The workflow is described as below:

![Figure 1. Location of SLS field in the ONWJ block](image1)

![Figure 2. Location of the wells in the SLS field](image2)
Figure 3. Workflow of the study

2.1 Initial analysis using acoustic impedance

On multiattribute analysis, AI will serve as external attribute. However, initial analysis on AI volume is required to obtain information on which parameter would be described the best. A crossplot between AI log and parameters such as density, porosity, Gamma Ray, and resistivity were made to determine AI sensitivity. As the result, the crossplot only show empirical connection between AI vs. porosity and AI vs. density meanwhile resistivity and Gamma Ray crossplots show no trend nor separation. In this study, a model-based inversion is performed. This inversion method compares the geological initial guess model with the seismic data. Based on the crossplot analysis, we can conclude that AI inversely related to porosity and directly to density. However, AI is incapable to sort out claystone and sandstone due to the overlapping Gamma Ray values as seen on figure 4.

Figure 4. Crossplot between acoustic impedance (x-axis) and porosity (y-axis) aided by Gamma Ray as color key to show any indication of separation.
Figure 5. Map of Al distribution. Target (Al < 20.000) is shown by light colours (green to yellow)

2.2 Multiattribute analysis

Multiattribute seismic analysis is a geostatistical method that combines more than one attribute to predicts physical properties of reservoir (Russell, 1997). Multiattribute analysis can be used to predict logs and volume. In this study, ten missing S-wave logs will be replaced with predicted S-log from multiattribute analysis. The only well with S-wave log is S-19 well. Multiattribute training process uses well data as input, original seismic as internal attribute, and AI inversion result as external attribute. We can set the number of maximum number of attributes on the subset and the operator length as we desired. However, to select the number of attributes to be applied on the predicted log, we need to be careful around the calculated error value. In this study, 9 attributes and 7 operator length were about to be used.

Figure 6. Multiattribute list with the training and validation error for each attribute

Figure 7. Comparison between original S-wave log (x-axis) and predicted S-Wave (y-axis). Correlation = 0.97.
2.3 Log transform and Lambda-Rho/Mu-Rho analysis

The predicted S-Wave logs are next transformed into Lambda-Rho and Mu-Rho logs using deterministic relationship as explained by the equations below:

\[
LR = AI^2 - 2.SI^2 \quad (1)
\]
\[
MR = SI^2 \quad (2)
\]
\[
SI = V_s \cdot \rho \quad (3)
\]
\[
AI = V_p \cdot \rho \quad (4)
\]

Where LR in (1) is Lambda Rho, MR is Mu-Rho, SI is Shear Impedance, and AI is Acoustic impedance. The transformed LR and MR then crossplotted against the same parameters as previously done on AI data. LR has poor capacity to characterize the target as the data distribution don’t show any trend nor separation. On the other hand, MR concluded as the better attribute to describe reservoir’s character because the crossplot shows good trend and separation. Therefore, we will only process Mu-Rho for further analysis.

Figure 8. Result of S-Wave prediction on 9 wells

Figure 9. Crossplot between Mu-Rho (x-axis) and resistivity (y-axis) aided by Gamma Ray as color key. A linear trend can be seen in the crossplot.

Figure 10. Crossplot between Mu-Rho (x-axis) and density (y-axis) aided by Gamma Ray as color key. Separation between high GR litology (claystone) and low GR (sandstone) can be seen in the crossplot.
3. Result and Discussion

Theoretically, Mu-Rho represents sensitivity of the rock’s matrix. Rocks with lower Mu-Rho tends to be more elastic compared to ones with higher Mu-Rho. Previous analysis on AI has given a hint that the good quality reservoir relates to lower impedance value and high porosity, yet the method gave not enough satisfying separation between claystone and sandstone. Sandstone reservoir is the main object in this study. Based on the crossplot, we are looking for areas in which the Mu-Rho value exceeds the cutoff \((7.5 \, \text{GPa} \cdot \text{s/cm})\) since cleaner sandstone can be characterized from high Mu-Rho. Combining the initial analysis from AI inversion and Mu-Rho attribute, the sandstone reservoir can be characterized based on its porosity and rigidity. Areas that consist of >20% porosity can be determined from low impedance character. Sharper analysis is shown by Mu-Rho result, which able to determine the clay content of the sandstone. The area that intersects between AI and Mu-Rho anomaly indicates good reservoir prospective area and feasible for further development.

![Figure 11](image-url)

Figure 11. Map of Acoustic Impedance distribution (a) and Mu-Rho distribution (b) extracted from the same target zone

4. Conclusion

(1) Multiattributes analysis can be considered as an alternative to predict \(V_s\) at which the log is absent.

(2) Mu-Rho gives better characterization of the SLS field compared to Lambda-Rho.

(3) Mu-Rho attribute is able to separate sandstone and claystone with cutoff value \(7.5 \, \text{GPa} \cdot \text{s/cm}\).

References

[1] Aveliansyah, Ponco, P., Triyono, W., Saefullah, U., (2016) Pre-Talang Akar Formation: New Hopes for Hydrocarbon Exploration in the Offshore, 2016 Indonesian Petroleum Association, Jakarta, Indonesia.

[2] Goodway, B., Chen, T., and Downtown, J., (1997): Improved AVO fluid detection and lithology discrimination using Lamé petrophysical parameters; “\(\rho\)” , “\(\mu\)” , and “\(\lambda/\mu\) fluid stack”, from P and S inversions: CSEG national convention, Expanded Abstracts, 148-151.
[3] Hampson, D. P., Schuelke, J.S., and Quirein, J. (2001): Use of Multiattribute Transforms to Predict Log Properties from Seismic Data, Geophysics vol. 66, hal 220-236.

[4] Ponto, C.V., et al. (1987): Controls on Hydrocarbon Accumulation in the Main and Massive Sandstones of the Upper Cibulakan Formation, Offshore Northwest Java Basin, 6th Regional Congress on Geology, Mineral, and Hydrocarbon Resources of Southeast Asia – GEOSEA VI, Jakarta.

[5] Russel, B.H., D. Schuelke, J. Qurein. (1997): Multiattribute seismic analysis, the Leading Edge, vol. 16, 1439-1443.