Classification Lithofacies Based on Petrophysics Properties and Clustering Algorithm in X Field

Asido Saputra1,*, M Puput Erlangga1, Handoyo1, Egie Wijaksono2

1 Geophysical Engineering, Institut Teknologi Sumatera, South Lampung, Indonesia
2 Center for Research and Development of Oil and Gas Technology (LEMIGAS), Jakarta, Indonesia

Corresponding author: asido.sigalingging@staff.itera.ac.id

Abstract. Lithofacies classification is one of the key modelling components in reservoir characterization. Log-facies classification methods aim to estimate a profile of facies at the well location based on the values of rock properties measured or computed in well log analysis (such as density, porosity, P-Wave, shale content and mineralogy). In this study, the classification of lithofacies was carried out in X field. The first step of classification lithofacies is cross-plot of each petrophysical data, the result of this step is used as a priori data to statistical facies classification (k-means algorithm). Lithofacies in this study were successfully separated into two facies namely sand and shale. The results obtained show that X Field is a gas saturated with sandstone as the main reservoir, especially in the Plover formation.

Keywords: Lithofacies, Petrophysical Properties, K-mean, Reservoir

1. Introduction

Classification of lithofacies is a key element in reservoir modeling. The lithofacies is done traditionally using a sedimentation. Detailed geological models of facies are very dependent on core sample at wells. However, these models are difficult to solve for all reservoir models because they need accurate assessment of wells. To open facies classification to all reservoir models, the facies log must be approved with good log data. In general, conventional reservoirs, log-formation classification depends on petrophysical curves performed in formation evaluation analysis (such as shale composition, porosity and mineralogy).

Further classification of lithofacies is needed to separate reservoir and non-reservoir zones. This research will be conducted lithofacies classification in X field. X Field is a gas producing field that has been producing with sandstone as the main reservoir, especially in the Plover formation [1].

2. Geology Setting

The Bonaparte Basin extends off the coast of Kununurra in the south, Ashmore Reef in the northwest, and Flinders Shoal in the north. The Bonaparte Basin covers an area of about 270,000 km². Approximately 20,000 km² is located on land between Cambridge Bay and Fog Bay. Administratively the Bonaparte basin is located in western Australia and belongs to the islands of Ashmore and Cartier.

Timor's regional stratigraphy is shown in Figure 2. The main source rock is in Late Triassic rocks in spooky formations and Jurassic in the Northwest Shelf (Peters et al., 1999). Reservoir based (Sani et al., 1995) is dominated by Late Triassic -Early Jurassic rocks in the Malita and Plover formations.
3. Method

This research data consists of one well, well data consists of several logs including gamma ray logs, bulk density, neutron porosity, saturated water, volume of shale and P, S wave. Each log is shown in Figure 3.
3.1 Lithofacies Definition

A gamma-ray log measures the total gamma radiation emitted by rocks. Shale and non-shale lithology will be easy to distinguish using gamma-ray logs. Shale will emit high gamma radiation compared to other rocks. Shale minerals tend to absorb large amounts of thorium, and the presence of potassium in the shale will result in high gamma radiation. Porosity can be measured using neutron porosity, by measuring the amount of hydrogen content in the rock along the borehole. The measurement of the hydrogen index is directly related to the porosity of the rock. Hydrogen can come from various sources, including organic materials, hydrogen can also come from mineral clays and water fluids that fill rock pores. [2]

P-wave can be directly calculated from the sonic log, the measurement is made by counting the delay time of sonic wave emitted by the transmitter and arrived at the receiver. P-Wave will propagate more slowly on clay and rocks which are saturated by water or hydrocarbon fluids. Fluid saturation in the rock will decrease the bulk modulus of the rock so that it will directly decrease the value of the wave velocity. Whereas in rock sandstones
which dominance by quartz minerals, it will have a higher wave velocity, this is the aim of bulk modulus of quartz is higher than that of clay.[2]

Based on the different characteristics of each log along with mineral changes, it can be used to classify lithology. Rock classification based on rock petrophysics is carried out by using a crossplot between each of the physical properties of the rock. It is hoped that the crossplot will collect the same minerals in the same zone. In addition, the lithological classification can also be done by creating a threshold for the gamma ray value that distinguishes shale and non-shale stones. Based on these two methods, lithology classification can be done on the data, shown in Figure 4.

![Figure 4. Facies definition based on petrophysical properties.](image)

### 3.2 Statistical Lithofacies Classification

The k-Mean algorithm is an algorithm used to cluster or classify data. Algorithms work by partitioning existing objects into one or more groups based on their characteristics, so that each object that has the same characteristics will be grouped into the same group, and other objects that have different characteristics will be grouped into other groups. K-Means clustering aims to minimize the objective function set in the clustering process by minimizing variations between data in a cluster and maximizing variation with data in other clusters, also aims to find groups in the data, with the number of groups represented by variable K. The algorithm for performing K-Mean clustering is as follows [3]:

1. Select K of the centroid points at random. In this case, the initials of the centroid were based on the results of the previous petrophysic analysis.
2. Group the data so that K clusters are formed with the centroid point of each cluster being the centroid point that has been previously selected. Grouping is based on the closest distance between the object and a centroid, equation 1.
3. Update the centroid point value. Update the centroid point based on the mean value of each centroid, equation 2.
4. Repeat steps 2 and 3 until the value of the centroid point no longer changes.

The process of grouping data into a cluster can be done by calculating the shortest distance from the data to a centroid point. Suppose each log data element, $x_{i1} = \text{P-wave -ith}$, $x_{i2} = \text{density -ith}$, $x_{i3} = \text{porosity -ith}$, $x_{i4} = \text{gamma ray -ith}$, and the centroid element obtained from the crossplot process, becomes the initial $x_j$ centroid, with the same configuration as for each log element. The Minkowski distance calculation can be used to calculate the distance between 2 pieces of data. The formula for calculating this distance is [3]:

$$d(x_i, x_j) = (|x_{i1} - x_{j1}|^g + |x_{i2} - x_{j2}|^g + \cdots |x_{ip} - x_{jp}|^g)^{1/g}$$  \hspace{1cm} (1)

Where:
- $g = 1$, for Manhattan distance,
- $g = 2$, for Euclidean distance,
\(x_i, x_j\) = two point of data that will be calculated the distance.

Updating a centroid point can be done with the following formula [4]:

\[
\mu_k = \frac{1}{N_k} \sum_{i=1}^{N_k} x_i
\]  

(2)

Where,
\(\mu_k\) = the new centroid point of the K-cluster,
\(N_k\) = number data of the K-cluster,
\(x_i\) = data i-th of the K-cluster

Table 1. Initial centroid (estimated) inputs to the k-Means algorithm. Estimation parameter based on cross-plot each petrophysical properties

| No | Facies | Gamma ray [API] | Density (gr/cc) | Neutron porosity | Log Sonic |
|----|--------|-----------------|-----------------|------------------|-----------|
| 1  | Shale  | 40              | 2.36            | 0.15             | 100       |
| 1  | Sands  | 35              | 2.53            | 0.23             | 82        |

4. Results And Discussion

The initial facies classification is based on multi-crosplot of each petrophysical properties, two facies can be identified, each of them is sandstone and shale. Then the average value will be used as initial input for the statistical classification of lithofacies. Each identification result based on a crossplot is shown in Table 1.

Table 2. Optimized centroid (estimated) inputs to the k-Means algorithm. The centroid is equal to mean each petrophysical properties

| No | Facies | Gamma ray [API] | Density (gr/cc) | Neutron porosity | Log Sonic |
|----|--------|-----------------|-----------------|------------------|-----------|
| 1  | Shale  | 37.74           | 2.41            | 0.12             | 102.26    |
| 2  | Sand   | 22.08           | 2.51            | 0.21             | 68.58     |

As shown in Figure 5 and Table 2, Shale has the most dominant gamma ray value with an average of 37.74 API, then Sandstone 22 API. From the density data, sand has a density value that is greater than shale with a density value of 2.51 gr/cc and shale density values of 2.41 gr/cc. Based on the porosity value of sandstone has the highest porosity value of 21% and shale of 12%.

Figure 6, shows a comparison between lithofacies from the statistical analysis (k-mean) to lithofacies based on direct observation. The correlation of the two lithofacies in Figure 6 is 73%, showing that the k-mean algorithm with a priori from petrophysics is quite accurate in the classification of log lithofacies. K-Mean algorithm with a priori from petrophysics analysis can reduce the possibility of the minimum error trapped at the local minimum, so that the resulting error is smaller.
Figure 5. Probability density function(pdf) of four petrophysical properties produced by k-means algorithm.
5. Conclusion

The k-Mean algorithm with a priori from petrophysical analysis can be a good delineated log lithofacies, give correlation with log lithofacies observation more than 70%. Clustering algorithm (k-Means) can be used to delineated lithofacies in wells around a-priori wells, so as to minimize costs because direct observation can be reduced.

References

[1] Keep, M., Longley, I. & Jones, R., 2002, Sumba and its effect of Australia_s northwest margin, in HILLIS, R.R. & MULLER, R.D., (Eds), The Evolution and Dynamics of the Australian Plate:Joint Special Publication of the Geological Society of Australia and the Geological Society of America, in press

[2] Glorioso, J. C., and A. Rattia, 2012, Unconventional reservoirs: Basic petrophysical concepts for shale gas: Presented at the SPE/EAGE European Unconventional Resources Conference and Exhibition, SPE-153004MS, doi: 10.2118/153004

[3] O. Maimon and L. Rokach, 2005, Data Mining and Knowledge Discovery Handbo- ok. Secaucus, NJ, USA: Springer-Verlag New York, Inc.