

# ESTIMATION OF 3D CARBONATE RESERVOIR PERMEABILITY AND INTERPARTICLE POROSITY BASED ON ROCK TYPES DISTRIBUTION MODEL

\*Mohammad Syamsu Rosid<sup>1</sup>, Rizky Achmad Kurnia<sup>2</sup>, and Mochamad Wahdanadi Haidar<sup>3</sup>

<sup>1,2</sup>Faculty of Mathematics and Natural Sciences, Universitas Indonesia, Indonesia

<sup>3</sup>Pertamina Hulu Energi, Indonesia

\*Corresponding Author:., Received: 14 April 2020, Revised: 01 May 2020, Accepted: 15 May 2020

**ABSTRACT:** Carbonate reservoir in “R” Oil Field is a reef limestone that has a very complex porosity and permeability characteristics caused by its diverse pore types (interparticle, stiff, and crack). This study aims to characterize the carbonate reservoir by estimating its interparticle porosity and permeability based on rock types distribution model. Modified Rock-Fabric Classification is used to determine the distribution of rock types in three reference wells (R2, R9, R20). Rock Types (RT) distribution model is generated by integrating Acoustic Impedance (AI) and Shear Impedance (SI) attributes from seismic simultaneous inversion with rock types distribution in reference wells using Naïve-Bayes Classifier. Three-dimensional (3D) interparticle porosity and permeability are then estimated from the rock types distribution model. The result shows RT3 which is characterized by crack pores as the most dominant rock type in the reservoir followed by RT5, RT4, and RT6 which are characterized by interparticle pores. Relatively high interparticle porosity values ranges from 0.18 to 0.22 can be associated with RT6 of mud-dominated packstone or wackestone. Meanwhile, relatively high permeability values range from 70 to 80 millidarcy (mD) can be associated with RT4 of grainstone. Laterally, there are clusters of spots in the south of the three reference wells that showed relatively high permeability value.

**Keywords:** Carbonate reservoir, Interparticle porosity, Modified rock-fabric classification, Permeability, Rock type

## 1. INTRODUCTION

Hydrocarbons which are hosted in carbonate reservoir rocks made up for almost 50% of oil and gas production worldwide. This brings a challenge for oil and gas exploration and field development especially for reservoir characterization because carbonate reservoir rocks such as limestone and dolomite have a high level of heterogeneity compared to clastic reservoir rocks such as sandstone [1]. This heterogeneity resulted from (i) intensive vertical and lateral facies variation and (ii) extreme diagenetic process. Thus, carbonate reservoir rocks have variations of both pore types (i) primary or interparticle and (ii) secondary (vuggy/stiff, and crack) and rock types [2,3]. Consequently, this results in high complexity of carbonate reservoir rocks characteristics that are related to porosity and permeability.

The complexity of carbonate reservoir rocks porosity and permeability means that to characterize carbonate reservoir rocks properly, we need a carbonate rock type classification method that enables us to estimate the permeability of the reservoir. There are many rock type classification methods such as Rock-Fabric Classification [4], Flow Zone Indicator [5], Winland R35, and Pore Geometry Structure. A previous study by Haikel *et*

*al.* [6] compared those methods by using them to determine carbonate rock types and estimating permeability. The result shows that a Modified Rock-Fabric Classification gives better separation between each rock type.

This study is intended to continue the previous study by applying the Modified Rock-Fabric Classification to get 3D Rock Type Distribution Model and using it as a guidance for Interparticle Porosity and Permeability estimation on “R” Oil Field.

## 2. METHODS

### 2.1 Rock-Fabric Classification

Rock-Fabric Classification method divides limestone reservoir with few secondary porosity fraction characteristics into three rock types based on interparticle porosity ( $\phi_{ip}$ ), permeability ( $k$ ), grain size, and sortation. In order to relate carbonate rock fabrics to pore-size distribution, it is important to determine that the pore space belongs to one of the three major pore-type classes, interparticle, separate-vug, or touching-vug. Each class has a different type of pore distribution and interconnection. In the absence of vuggy porosity, pore-size distribution in carbonate rock can be

described in terms of particle size, sorting, and interparticle porosity [7]. Grain size and sortation are represented by rock-fabric number ( $rfn$ ). Boundaries for each rock type can be obtained through Eq. (1) [4].

$$\text{Log}(k) = (A - B \text{Log}(rfn)) + ((C - D \text{Log}(rfn)) \text{Log}(\phi_p)) \quad (1)$$

where:

$A = 9.7982$ ;  $B = 12.0838$ ;  $C = 8.6711$ ;  $D = 8.2965$ ;  $rfn$  = rock-fabric number;  $\phi_p$  = fractional interparticle porosity.

## 2.2 Naive Bayes Classifier

Naive Bayes Classifier is a supervised machine learning algorithm based on Bayes's Theorem. This theorem assumes that a feature is independent and not related to the presence of other features in the same data [8]. Probability for each rock type based on Bayes's Theorem can be computed using Eq. (2) [9, 10].

$$P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)} \quad (2)$$

where:

$P(Y|X)$  = posterior probability;  $P(X|Y)$  = data trends;  $P(Y)$  = probability of class.

The boundaries of each rock type are modeled by the classifier as a window span using Gaussian Probability Density Function.

## 2.3 n-Fold Cross-Validation

Cross-validation is a method to estimate the error rate of a machine learning algorithm using the available training data, in the absence of a very large designated test set. The method of cross-validation used in this study is n-Fold. This method works by dividing the available data set into n number of folds of approximately equal size. The first fold is treated as a validation set and the remaining  $n - 1$  folds are treated as a training set. The mean square error (MSE) is computed on the held-out fold. This procedure is repeated n times until all folds had been treated as a validation set.

## 3. RESULTS AND DISCUSSION

### 3.1 Rock Type Classification on Reference Well Data (Modified Rock-Fabric Classification)

In complex carbonate reservoirs, rock permeability cannot be determined by porosity only. Rock typing methods can be used to determine rock types and estimate rock permeability. The method can generate rock permeability-porosity correlation.

Results from [6] shows there are many data with low interparticle porosity fraction that fall outside

the three rock types [4]. It suggests that there are high secondary porosity fractions in this study area. The existence of this pore type in a carbonate reservoir results in reduced interparticle porosity fraction which can result in misclassification. Therefore, further efforts need to be made to overcome this problem.

An effort was made to overcome this problem by modifying Rock-Fabric Classification [6]. Modification was made by adding four new rock types subjectively according to the data distribution trend to accommodate many data that fall outside the three original rock types. It resulted in a modified Rock-Fabric Classification with six rock types. In this study, we used their modified Rock-Fabric Classification on three reference wells (R2, R9, R20).

### 3.2 Data Training (Naïve-Bayes Classifier)

Training on Naïve-Bayes Classifier is carried out by using two approaches (i) Acoustic Impedance (AI) and Shear Impedance (SI) from reference well data as a proxy variable for input parameters and (ii) rock types from modified rock-fabric classification as a supervision label. The performance of the training model can be presented quantitatively by using cross-validation and confusion matrix. Cross-validation is performed using a 10-fold cross-validation method. The result shows the model has an accuracy of 62.75%.

The amount of data from each Rock Type (RT) that is correctly and incorrectly classified in the cross-validation process can be visualized using the confusion matrix in Table 1. In the confusion matrix, the column shows true rock types while the row shows predicted rock types. The amount of correctly classified data on each rock type is presented in the diagonal section of the matrix. Meanwhile, incorrectly classified data is presented on the outside of the diagonal.

Table 1 Confusion matrix of training model using AI-SI (adapted from [6]).

RT	1	2	3	4	5	6
1	16	4	1	0	0	0
2	9	36	11	1	0	0
3	0	9	13	4	0	0
4	0	1	3	35	10	1
5	0	0	1	21	30	6
6	0	0	0	2	8	25

### 3.3 Rock Type Classification on Seismic Attributes

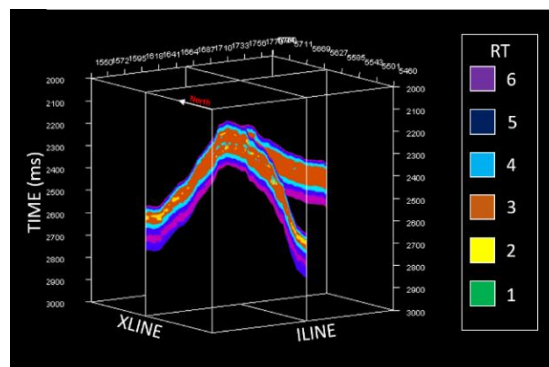
Acoustic Impedance (AI) and Shear Impedance (SI) attributes from seismic simultaneous inversion result by [11] are used as an input in Naïve-Bayes

Classifier model previously made to classify and create a rock type model. The classification of AI and SI seismic attributes is performed using trace-by-trace iteration from inline 1550 to 1794. The classification results are then compiled into a 3D rock types distribution model as shown in Fig.1. A slice of the 3D rock type distribution model on inline 1677 is shown in Fig.2.

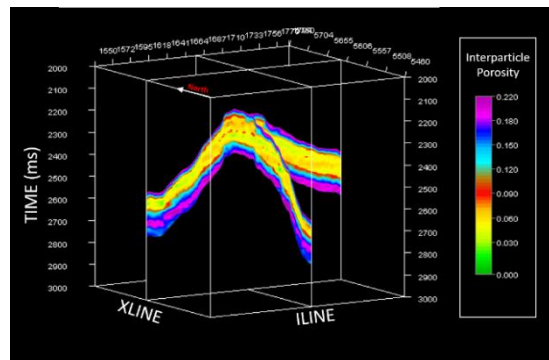
Fig.1 shows a 3D seismic section of the results of modeling the distribution of rock type, interparticle porosity, and rock permeability in the study area. The zone of interest is dominated by rock type of RT3. However, the RT3 is not a rock type that has the highest value of both parameters of porosity and permeability. The highest rock porosity in the area is rock type of RT6, while the

highest permeability is in RT4 rock. A detailed explanation of each parameter is given in the appropriate sections.

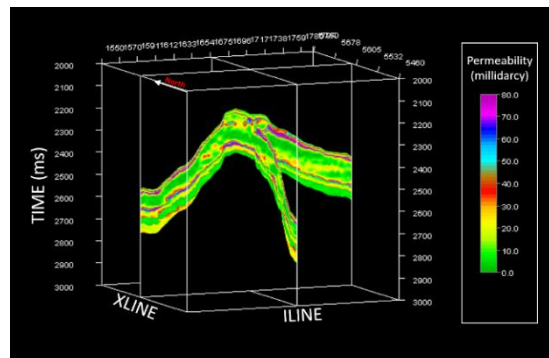
Vertical distribution of rock types from top to base horizon of the reservoir as shown in Fig.2 is as follows, RT5, RT4, RT3, RT4, RT6, and RT5. Meanwhile, the distribution of rock types in the lateral direction is relatively more homogeneous. The abundance of RT3 in this reservoir indicates that the reservoir has pore type characteristics that are thought to be dominated by both crack secondary porosity and interparticle porosity. This result shows compatibility with pore type distribution from [3].



(a) 3D Rock Type Model



(b) 3D Interparticle Porosity Model



(c) 3D Permeability Model

Fig.1 The results of the 3D Model in the “R” oil field.

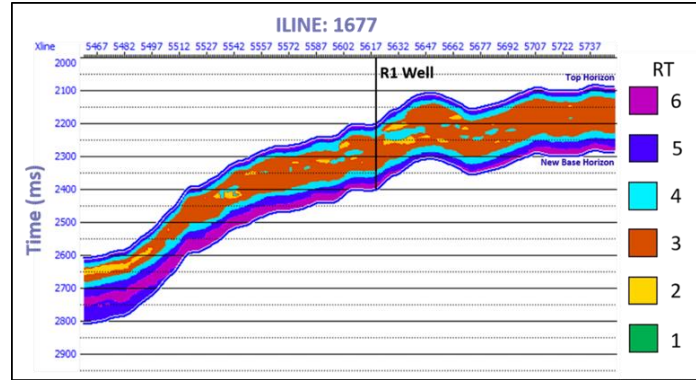


Fig.2 Rock Type distribution on inline 1677.

### 3.4 Interparticle Porosity and Permeability Estimation

The relationship between interparticle porosity and permeability with Acoustic Impedance (AI) for each rock type from well data is obtained by making a cross-plot of the two variables. An inversely proportional relation is generated. Then, linear regression is applied to obtain the interparticle porosity and permeability equation as a function of AI for each rock type in Table 2

Relatively high and good correlation coefficient of  $R^2$  on RT4 – RT6 is thought to be due to these rock types have pore type characteristics which are dominated by interparticle porosity. This arises from the fact that based on the Rock-Fabric Classification made by [4], RT4 is a grainstone, RT5 is a grain-dominated packstone, and RT6 is a mud-dominated packstone or wackestone, all of which have characteristics dominated by primary porosity (interparticle). Meanwhile, a relatively low correlation of  $R^2$  values on RT1 – RT3 is thought to be due to a dominant secondary porosity (stiff and crack) characteristics in these rock types. The presence of secondary porosity is thought to cause heterogeneity of the pore type more complex and the accuracy of determining the rock type is lower.

The obtained equations are then used to estimate interparticle porosity and permeability on the 3D AI

seismic attributes guided by the 3D rock type distribution model previously made. The estimation of AI seismic attributes is performed using a trace-by-trace iteration from inline 1550 to 1794. The estimation results are then compiled into a 3D interparticle porosity and permeability model as shown in Fig.1.

A slice of the 3D interparticle porosity model and permeability on inline 1677 is shown in Fig.3 and Fig.4 respectively. This inline is chosen to visualize the result because it traverses R1 well which used as a reference for rock typing and calibrating interparticle porosity and permeability.

The result of interparticle porosity and permeability estimation as shown in inline 1677 shows that the study area has interparticle porosity value ranges 0.04 – 0.22 and permeability ranges 0 – 80 mD. Overall, the distribution pattern of estimated interparticle porosity and permeability relatively fits with the distribution of rock types.

The relatively good results of interparticle porosity estimation with values around 0.18 – 0.22 are associated with RT6 which is categorized as interparticle porosity and consists of mud-dominated packstone or wackestone. Meanwhile, relatively good estimated permeability values around 70 – 80 mD are associated with RT4 which categorized as interparticle porosity and consists of grainstone.

Table 2 Interparticle Porosity and Permeability Equation for each rock type

RT	Interparticle porosity ( $\phi_{ip}$ )	$R^2(\phi_{ip})$	Permeability ( $k$ )	$R^2(k)$
1	$\phi_{ip} = -0.000003(AI) + 0.1953$	0.143	$k = 33.023(\phi_{ip})^{0.2095}$	0.0139
2	$\phi_{ip} = -0.000007(AI) + 0.3906$	0.416	$k = 27.038(\phi_{ip})^{0.3966}$	0.0126
3	$\phi_{ip} = -0.000005(AI) + 0.2944$	0.259	$k = 7 \times 10^8(\phi_{ip})^{6.6194}$	0.3082
4	$\phi_{ip} = -0.000008(AI) + 0.4635$	0.544	$k = 6 \times 10^6(\phi_{ip})^{5.7263}$	0.6508
5	$\phi_{ip} = -0.000007(AI) + 0.4301$	0.591	$k = 29037(\phi_{ip})^{5.3967}$	0.7969
6	$\phi_{ip} = -0.000010(AI) + 0.5427$	0.908	$k = 7886.5(\phi_{ip})^{4.4161}$	0.8362

Quantitatively, the distribution of the results of interparticle porosity and permeability estimation can be analyzed using a histogram plot as shown in Figs.5,6 respectively. From the histogram, we can see the distribution of estimated interparticle porosity and permeability values in the reservoir. It can be observed that the dominant interparticle porosity value is about 0.08 while for permeability is about 5 mD.

Laterally, the distribution of estimated interparticle porosity from the model is more

homogenous than its vertical distribution. This observation means that the reservoir is in the form of layers of different carbonate rock types that accumulated vertically.

The result of permeability estimation from the model can also be observed using the rms average map in Fig.7. The figure shows clusters of spots marked with dark blue to purple color that represents a relatively high permeability value in the southern of R2, R9, and R20 wells.

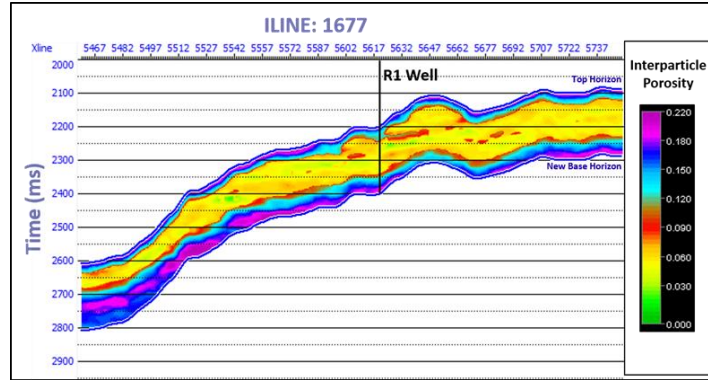


Fig.3 Interparticle Porosity distribution on inline 1677.

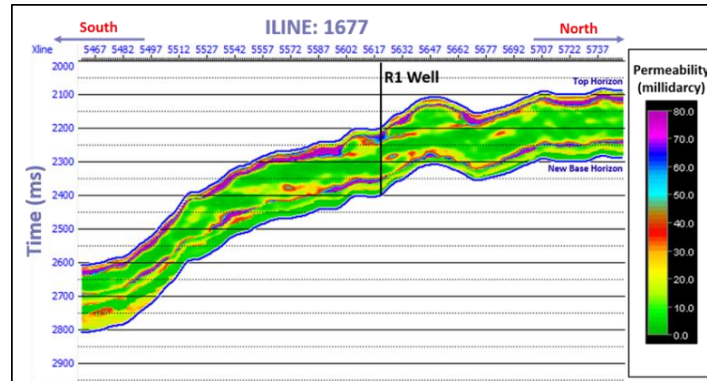


Fig.4 Permeability distribution on inline 1677.

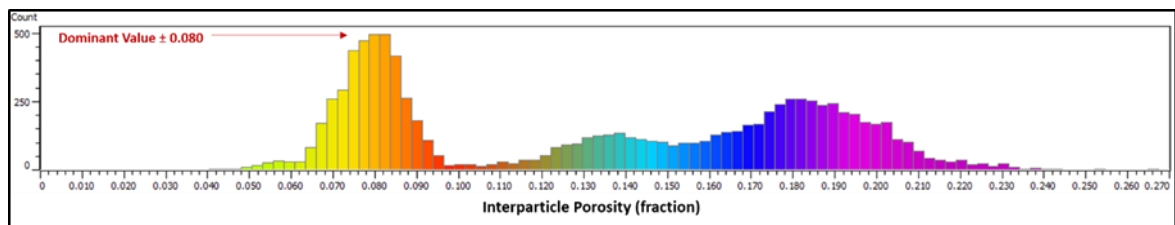


Fig.5 Histogram plot of 3D Interparticle Porosity Model.

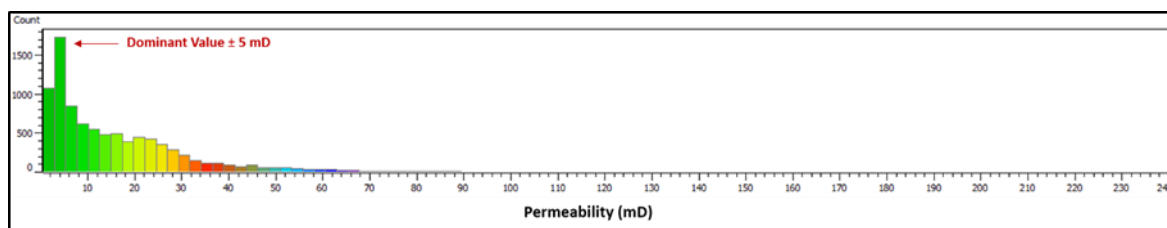


Fig.6 Histogram plot of 3D Permeability Model.

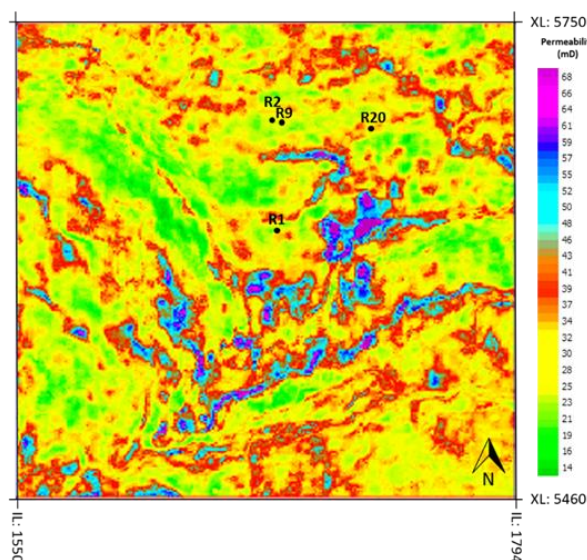


Fig.7 RMS average of Permeability Model map.

#### 4. CONCLUSION

The results showed a three-dimensional (3D) distribution model of rock types, interparticle porosity, and permeability. Based on the 3D rock types distribution model, it can be concluded that the carbonate reservoir in “R” Oil Field is dominated by rock type of RT3 which has crack secondary porosity characteristics. Relatively good interparticle porosity values are associated with RT6 of mud-dominated packstone or wackestone. Relatively good permeability values are associated with RT4 of grainstone. Laterally, the high permeability rocks are spread in the form of clusters of spots in the south of R2, R9, and R20 wells.

#### 5. ACKNOWLEDGMENTS

The publication of this work has been funded by the DRPM Universitas Indonesia through a very meaningful grant of PITTA 2019. We also thank PT. Pertamina - Petro China East Java for permission to use data in this study. Thanks to Panji, Syem, and Fauzi for their togetherness in encouraging each other during the processing of this data.

#### 6. REFERENCES

- [1] Xu S., and Payne M.A., Modeling Elastic Properties in Carbonate Rocks. The Leading Edge, Vol. 28, Issue 1, 2009, pp.66-74.
- [2] Lubis L.A., and Harith Z.Z.T., Pore Type Classification on Carbonate Reservoir in Offshore Sarawak using Rock Physics Model and Rock Digital Images. IOP Conference Series: Earth and Environmental Science, 19, 2014.
- [3] Rosid M.S., Augusta F.F., and Haidar M.W., Journal of Physics: Conference Series, 1013, 2018.
- [4] Lucia F.J., Carbonate Reservoir Characterization (New York: Springer), 2007.
- [5] Enaworu E., Ajana L.O., and Orodu O.D., Permeability Prediction in Wells Using Flow Zone Indicator (FZI). Open Access J. 58, 2016, pp.640-645.
- [6] Haikel S., Rosid M.S., and Haidar M.W., Study Comparative Rock Typing Methods to Classify Rock Type Carbonate Reservoir Field “S” East Java. Journal of Physics: Conference Series, Vol. 1120, 2018.
- [7] Lucia F.J., Rock-Fabric/Petrophysical Classifi

- cation of Carbonate Pore Space for Reservoir Characterization. The University of Texas at Austin, Texas. 1993.
- [8] Goncalves E.C., da Silva P.N., Silveira C.S., Carneiro G., Domingues A.B., Moss A., and Azeredo R.B.d.V., *Journal of Applied Geophysics*, 140, 2017, pp.93-101.
- [9] Scales John A., Smith Martin L., and Treitel S., *Introductory Geophysical Inverse Theory*, Samizdat Press, Colorado, 2001, pp.71-89.
- [10] Rosid M.S., Haikel S., and Haidar M.W., Carbonate Reservoir Rock Type Classification using Comparison of Naïve Bayes and Random Forest method in field “S” East Java. *AIP Conference Proceedings*, Vol. 2168, 2019.
- [11] Reza M.F., Rosid M.S., and Haidar M.W., Carbonate Reservoir Characterization using Simultaneous Inversion in Field “X”. *AIP Conference Proceedings*, Vol. 2168, 2019.

---

Copyright © Int. J. of GEOMATE. All rights reserved, including the making of copies unless permission is obtained from the copyright proprietors.

---