Pore type-based carbonate reservoir characterization using rock physics modeling of “RF” field North Sumatera Basin

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Abstract. Heterogeneity and Complexity are the main reasons why carbonate reservoirs offer a great challenge for its characterization compared to siliciclastic reservoirs. Carbonate reservoirs are known for its variable pore type and this variability can affect the Vp value up to 40 %. Pore type can vary depending on its depositional environment and diagenetic processes and these pore types are highly correlated with permeability. Differential Effective Medium is used to model the elastic modulus of effective medium that takes into account the effect of complexity of rock pore type. This complexity, in modeling, is divided into three geophysical pore types, which are stiff pore, interparticle pore, and microcrack. The resulting rock physics model is then used to calculate the value of Vs. Pore type inversion shows that the dominant pore types in this study area are interparticle and microcrack. The results of 1D modeling are then distributed to seismic volume to map the spatial distribution of pore type. Sensitivity analysis shows that acoustic impedance, shear impedance, and porosity have a good correlation with pore type. Therefore, Probabilistic Neural Network is used to distribute 1D pore type to seismic volume by using acoustic impedance, shear impedance, and porosity as a training data. The resulting volume is then used to interpret the zones with best permeability.

Keywords: Carbonate reservoir characterization, differential effective medium, rock physics model, pore type, probabilistic neural network

1. Introduction
Carbonate reservoirs are considered as a host for oil and gas accumulation, making up almost 60 % of the world proven reserves [1]. The main problem in carbonate reservoir characterization lies in identifying the producible and economically good reserves [1]. This challenge appears as a consequence of carbonate heterogeneity, that is, in one depositional sequence and diagenetic processes, this reservoir is not only different in its storage capacity, but also on its pore characteristic [2].

Information about economic reserves can be understood by its producibility. Information about producibility, beside from rock porosity, can be acquired through its permeability that is highly correlated with pore structure in complex carbonate rocks [3-5]. Carbonate rocks can have a more complex pore structure than siliciclastic rock. Choquette and Prays divided pore type in carbonate into 15 classes which each genetically or physically different [6]. This pore complexity in carbonate rocks, in the modeling, is divided into three representative geophysical pore type, which are moldic, vuggy,
and interparticle. Because this complexity of pores is controlled by diagenetic processes and it gives clues about permeability, pore structure prediction can give a very insightful information about the characteristic of the reservoir.

The science of Rock physics creates a link between elastic properties (e.g. Vp/Vs ratio, elastic modulus), reservoir properties (e.g. porosity, saturation, pressure) and reservoir architecture (e.g. lamination, and fracture) [7]. The complexity of pore type in carbonate rocks that is mentioned earlier can affect the seismic primary velocity up to 40% [8]. This complexity gives an implication to scattering in porosity-velocity relationship in carbonate rocks.

By implementing differential effective medium theory in rock physics modelling, an effective medium can be constructed that takes into account the effect of pore geometry. Many researchers have already applied this theory because it gives a higher porosity range (that is allowed) to construct an effective medium model and calculate its elastic modulus. This, can be achieved, by incrementally adding small inclusion until the desired porosity is reached. Therefore in this study, we implement this theory to construct the effective medium model.

Finally, in this work, we want to model the distribution for better understanding to the spatial distribution of pore type, the resulting 1D model are distributed to seismic volume by implementing neural network. In this work, from the pore type distribution volume, we want to infer the best permeable zones and possibly the geological history of this study area.

2. Materials and method

In this work, the 3D pre-stack seismic data was used along with the two wells which located in offshore part of North Sumatera Basin. The position of the two wells in seismic data are shown in figure 1. The fluid parameters at reservoir condition that were used for this modeling is shown in table 1.

![Figure 1. Position of the wells on seismic data.](image)

| Fluids   | Rho (gr/cc) | Vp (ft/s) | K (Gpa) |
|----------|-------------|-----------|---------|
| Water    | 0.99        | 5122.1    | 2.412   |
| Oil      | 0.8         | 3954.67   | 1.163   |
| Gas      | 0.103       | 1433.56   | 0.02    |

Table 1. Elastic properties of fluid that is used in the modeling from laboratory data.
2.1. Pore types in carbonate

Dunham, Choquette et al., and Lucia said that pore type in carbonate can be divided based on grain size, diagenetic, and its geometric complexity [4, 6, 9]. However, in modeling, according to Xu et al. [8], three geophysical pore types are used which reasonably great in representing complex carbonate pore types, which are [1]:

1. Reference pores, considered as a dominant pore type, representing interparticle and intercrystalline pores. They have a moderate aspect ratio and generally between 0.12–0.15.
2. Stiff pores, representing moldic and vuggy. They have a high aspect ratio usually above 0.7.
3. Cracks, representing micro-fractures and microcracks. They have low aspect ratio and generally between 0.01–0.02.

2.2. Voigt-Reuss-Hill method

To calculate the elastic modulus of mixture of various mineral, Voigt-Reuss-Hill method can be used. Voigt-Reuss-Hill method will create a solid rock that will be used in Xu et al. modeling with the formulation as follow [10]:

\[ M_v = \sum_{i=1}^{N} f_i M_i \]  
\[ \frac{1}{M_R} = \sum_{i=1}^{N} f_i \]  
\[ M_{VRH} = \frac{M_v + M_R}{2} \]

where \( M_v \) is the Voigt Bound, \( M_R \) is the Reuss Bound, \( f_i \) is fraction of i-th phase, \( M_i \) is the elastic modulus of i-th phase and \( M_{VRH} \) is the elastic modulus of mineral mixture.

2.3. Wood relation

To calculate bulk modulus of fluid mixture, following equation can be used [10]:

\[ \frac{1}{K_{fl}} = \frac{S_w}{K_w} + \frac{S_{oil}}{K_{oil}} + \frac{S_{gas}}{K_{gas}} \]

where \( K_{fl} \) is the elastic modulus of fluid mixture, \( S_w, S_{oil}, S_{gas} \) is the saturation of water, gas, and oil, \( K_w, K_{oil}, K_{gas} \) is the bulk modulus of water, gas, and oil respectively.

2.4. Gassmann’s relation

To calculate elastic modulus of \textit{saturated rock} from \textit{dry rock}, Gassmann’s theory can be used, by following equation [10]:

\[ \frac{K_{sat}}{K_0 - K_{sat}} = \frac{K_{dry}}{K_0 - K_{dry}} + \frac{K_{fl}}{\phi(K_0 - K_{fl})}, \quad \mu_{sat} = \mu_{dry} \]

where \( K_{dry} \) is effective bulk modulus of \textit{dry rock}, \( K_{sat} \) is modulus \textit{bulk} effective \textit{saturated-rock}, \( K_0 \) is bulk modulus of mineral constituent, \( K_{fl} \) is elastic modulus of mixed pore fluids, \( \phi \) is porosity, \( \mu_{dry} \) is effective shear modulus \textit{dry rock}, \( \mu_{sat} \) is effective shear modulus of saturated rock.
2.5. Rock physics model in carbonate

To quantify the effect of pore type in carbonate rocks, rock physics modeling is conducted based on the Differential Effective Medium theory to calculate the effective elastic moduli of carbonate rocks. The Differential Effective Medium theory, according to Zimmerman et al., Norris et al., and Cleary et al. creates a model of two-phase composite by adding inclusions of phase 2 incrementally into matrix phase (phase 1) [11-13]. This process continues until the desired proportion is achieved. The coupled-system of ordinary differential equation for calculating the effective elastic moduli, are, [14]

\[
(1 - y) \frac{d}{dy} (K^* (y)) = (K_2 - K^*) P^* (y) 
\]

(6)

\[
(1 - y) \frac{d}{dy} (\mu^* (y)) = (\mu_2 - \mu^*) Q^* (y) 
\]

(7)

with initial condition \(K^* (0) = K_1\) and \(\mu^* (0) = \mu_1\), where \(K_1\) and \(\mu_1\) is the bulk and shear modulus of host material, \(y\) is concentration of phase 2, \(P\) and \(Q\) is geometry factor.

2.6. Pore type quantification

Heterogeneity is the main challenge in carbonate reservoir characterization. Factors controlling sonic velocity are very complex compared to siliciclastic. Among them are intrinsic factor such as, mineralogy, susceptibility to alter, porosity, pore geometry, pore fluid, and also extrinsic factor such as compaction [3]. Pore geometry becomes important factor affecting elastic properties of the carbonate rocks [3, 15].

Following the model proposed by Xu et al. (figure 2) in which we classify clean carbonate pore types into three geophysical pore types that is mentioned earlier [8]. Firstly, mix the mineral constituents by using Voigt-Reuss-Hill average. Then add various inclusions by implementing the Differential Effective Medium theory to create dry rock. The dry rock is then saturated with fluid mixture (calculate using wood’s suspension model) by using Gassmann’s fluid substitution theory to create a fluid saturated rock model. In this process, the pore type proportion is gained by following the optimization process (figure 2) proposed by Kumar et al. [16]. The control of this process is the P-wave velocity.

![Figure 2. Illustration of rock physics model proposed by Xu et al. [8]. On the right side of figure is the illustration of the optimization process following the work of Kumar et al. [16].](image_url)
The final products of this modeling are the elastic modulus of effective medium. The elastic modulus of effective medium is then used to calculate the shear wave velocity.

The resulting 1D pore types are then distributed to seismic volume by using neural network with the input parameters are following the proposed scheme by Zhao et al. [1]. In his work, the parameters that were used for extracting the pore type volume from seismic data were P-impedance, S-impedance from pre-stack seismic inversion, and Porosity from neural network analysis from multiple attributes [1].

3. Results and discussion

3.1. 1D pore type inversion

The scattering in porosity-velocity relationship in this study area indicates that the pore type is not only composed of interparticle pores [3]. Three geophysical pore types are used as a representative of pore complexity in carbonates, which are interparticle pore, microcrack, and stiff pore [1]. Each pore type gives different response in term of elasticity. Stiff pores and interparticle pore tend to have a strong rock frame [3, 8, 17]. This characteristic makes the rocks are hard to deform thus resulting a high velocity response. However, microcrack, the most compliant pores with less compact frame that is caused by its flat shape will give a relatively lower velocity than stiff pores and interparticle pores [3, 8].

From this study area, it is shown that all the data from well RF-1 and well RF-2 (figure 3) are below the wyllie time average indicating that the pores are composed by microcracks and interparticle only. As mentioned earlier, the pore types proportion is resulted from optimalization process. By initially creating reference velocity (rocks consisting 100 % reference pores), the optimalization process continues until the modeled P-wave velocity is optimized to fit the measured P-wave velocity (sonic log). The result of this process is the pore type proportion along with elastic modulus of effective medium. Therefore, shear wave velocity can also be calculated by the end of this process. The resulting optimalization process is shown in track 3 of figure 4. The correlation between Vp measurement and Vp model, in both wells, are 0.999 which means the optimalization process has been successfully carried out. It can be seen that, in the two wells, the pore types are composed by interparticles and microcrack (microporosity in some depth) and in agreement with the description in the final well report. In some cases, high crack value is associated with dolomite as shown in well RF-1 (figure 4 red-squared zones). It is caused by the brittleness behaviour of dolomite.

![Figure 3. Scattered porosity-velocity relationship in well (a) RF-1 and (b) RF-2.](image-url)
Figure 4. (a) The upper part is well RF-1, and (b) the lower part is well RF-2. Pore types proportion are shown in track 3 (where blue is microcrack and white is reference pore). Log Vp and Vs are shown in track 4. Mineral and fluid content are shown in track 2. The red-squared zones in well RF-1 are zones with high microcrack volume associated with dolomite that is interpreted as a best permeable zones.

To correctly predict the Vs value, it is important to have the right Vp-Vs relationship [8]. The calculated Vs values are then correlated with the Vp value. The Vp-Vs relationship as shown in figure 5, well RF-1 has a nearly linear correlation, however detailed calculation shows that quadratic regression approach shows a little higher correlation. It proves that the lithology content is calcite as observed Vp-Vs relationship by Castagna et al. [18]. The nearly linear correlation could be possibly
caused by dolomites occurrence. The observed relationship in well RF-2 is more non-linear than in RF-1. It is caused by the mineralogy content in RF-2 that are composed dominantly by Limestone. Dolomite only occurs as a thin layer at the depth of 4000 ft. This non-linear relationship is in agreement with observed Vp-Vs relation by Castagna et al. [18]. The resulting Log Vs and Log Vp can be seen in figure 4 track 4.

3.2. Spatial distribution of pore type

In this study area, resulting pore types from 1D rock physics modeling are microcrack and interparticle and its log volume. The resulting 1D pore types, are then distributed to seismic volume by neural network analysis from multiple attributes. Sensitivity analysis shows that P-impedance, S-impedance, and Porosity shows a correlation of 0.89 with interparticle pores volume. These parameters that were used are similar with the parameters proposed by Zhao et al. [1]. Therefore, in this work, for distributing 1D pore type volume, Neural Network analysis is used for predicting the interparticle pores volume from the seismic data. The input parameters for training are elastic impedance (Zp, Zs) derived from simultaneous inversion pre-stack seismic data, and Porosity derived from neural network from multiple seismic attributes and resulting a correlation coefficient of 0.92. The inverted elastic impedance can be seen in figure 6. The resulting reference pore volume is shown in figure 7b. The microcrack volume is the complementary value of volume reference pore (i.e. volume reference pore + microcrack = 1).

As shown in figure 7b, reference pore (interparticle) is dominating the lower part of the section (purple colored). High proportion of reference pore in this zone is caused by its lithology that is grading carbonate to sandstone. Packstone is dominating in all depth of the well and commonly consisting dominantly interparticle pores. It is also shown, from the section of interparticle pores, the proportion of interparticle pores are all above 0.8.

High proportion of microcrack can be seen in the middle and upper part of carbonate and most likely is caused by compaction, tectonic compression, and/or the existence of faults because the study area is located in the tectonically active area. But the interpretation must carefully be taken from this high volume of microcrack as it can be possibly constituted by microporosity that commonly found in Lime Mudstone and Packstone due to their similar low velocity response [3, 8]. As can be found in well RF-1, the Lime Mudstone dominates in the interval 3530–3580 ft. Lime Mudstone with microporosity tends to have low permeability in contrast from microcrack.

![Figure 5. Vp-Vs relationship in (a) well RF-1 and (b) well RF-2. Blue lines in both wells are a non-linear trend.](image)
Figure 6. Cross section of the inverted P-impedance $Z_p$, (a) and S-impedance $Z_s$, and (b) the carbonate interval is between Malacca (top carbonate) and pra-tertiary (base carbonate).

Figure 7. Cross section of the (a) porosity and (b) reference pore volume.
The middle part of the carbonate that is dominated by dolomite shows relatively a bit higher of microcrack volume than the upper part that is dominated by Limestone. This most likely is caused by the brittleness of dolomite that gives this response when compaction and/or tectonic compression occurs. The map in figure 8 shows the lateral distribution of volume reference pore on the top horizon and middle part of carbonate. The lateral distribution in the upper part of carbonate as can be seen in figure 8, microcrack volume (lower ref pore, green-yellow red colored zone) is found in the surrounding of well RF-1 and also in well RF-2. High microcrack volume in the middle part of carbonate (red colored zone) can also be seen in the surrounding of well RF-1 and well RF-2 and shows southeast-northwest trend.

The overall distribution of pore type as can be seen is dominated by interparticle and microcrack. Microcrack in this study area is most likely to be caused by tectonic activity in this area. Tectonic compression that have already occured since Miocene up till now along with uplifting is the main control on these occurence of microcrack. In general, the higher microcrack will enhance permeability dramatically [1]. Dolomite, with high volume of microcrack (red-squared zone in figure 4 and red-colored zone in figure 7b and figure 8b, can be considered as a permeability sweet spot which is zone with relatively best permeability. However, advanced analysis need to be conducted and also core analysis for identifying more thoroughly and also correlating permeability with pore types and porosity quantitatively.

4. Conclusion
In this work, we have created 1D rock physics model using petrophysical data from 2 wells in North Sumatera Basin. 1D pore type inversion has successfully carried out with correlation between Vp model and Vp measurement is 0.999 in both wells. The result shows that in both wells are constituted by interparticle pore and microcrack. Using this rock physics model, Vs value can also be calculated. The correlation between Vp and Vs, in both wells, shows higher correlation when using non-linear approach as it is composed by Limestone.

In this work, we also distribute the 1D pore type using neural network where P-impedance, S-impedance, and Porosity are used as a training data. The resulting spatial distribution shows that in the lower part of carbonate has the highest value of reference pore (interparticle pore) as it is already grading to sandstone. As we already know that sandstones are constituted by interparticle pore. The relatively higher microcracks volume (lower reference pore) are found in the upper and middle part

![Figure 8](image_url)
of carbonate. The middle part of carbonates that is mainly composed by dolomite, with highest microcrack volume can be interpreted as a best permeability zone.

Finally, in this work we only use 1D rock physics model which means that if there are only two pore types encountered in the 1D, then so do in the 3D seismic. In our future work, we will try to use 3D rock physics model to extract pore type from seismic data as it can be applied more generally in any study area.

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