Seismic multiattribute for predicting reservoir properties: Case study of globigerina limestone reservoir, Madura Strait

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Abstract. Hydrocarbon exploration requires comprehensive understanding of geological and geophysical properties of subsurface reservoir. Therefore, subsurface rock properties determination, which include total and effective porosity, clay content, and water saturation, is a very important, particularly for reservoir target. In term of spatial coverage, subsurface rock properties are then distributed by using seismic multiattribute, which is performed in two approaches – linear multivariate regression and probabilistic neural network (PNN). Linear multivariate regression seismic multiattribute assumes that the relation of seismic attributes and reservoir property is linear, while probabilistic neural network, seismic multiattribute assumes non-linear relationship. This research employed linear multivariate regression using internal attribute of seismic data to predict several rock properties. Transformation of seismic internal attribute to rock properties was attained by a series of weights derived by least-squares minimization. To estimate the reliability of the derived multiattribute transform, cross validation is used where each well is systematically removed from the training set, and the transform is rederived from the remaining wells. The prediction error for the hidden well is then calculated. The validation error, which is the average error for all hidden wells, is used as a measure of the likely prediction error when the transform is applied to the seismic volume. This method was applied to Globigerina Limestone reservoir in Madura Strait that resulted in good prediction of reservoir properties. Result of this research is used for quantification of remaining lead and prospect in the field area. Furthermore, the predicted subsurface rock properties are used as input to optimize in developing well in the proven fields.

1. Introduction

The study area is located within the southern part of North East Java Basin in Madura Strait, one of the most prolific hydrocarbon basins in Indonesia. Within the study area, four wells have been drilled and penetrated reservoir from Early Pliocene age. Two wells (H-1 and K-1) had succeed in finding hydrocarbon from bioclastic limestone reservoir, which is mainly composed by Globigerina planktonic foraminifera tests/shell and one well (J-1) only encountered tight reservoir. This high uncertainties issues of Early Pliocene Globigerina reservoir in North East Java Basin might related to structure, reservoir heterogeneity and compartmentalization [1].

In general, the Pliocene commercial reservoir is a carbonate where the framework-grain is composed almost entirely of Globigerina tests/shells with matrix of calcareous muds [2]. Pore-system is
represented by dominantly interparticle porosity, formed in between foraminifera tests, and intraparticle porosity, contained within foraminifera chambers, with additional micro-intercrystalline type. Most of the intraparticle pore is capable to produce hydrocarbon due to interconnections provided by the foraminifera “aperture” and “punctae” within the skeletal wall. Figure 1 shows the scanning Electron Micrograph of individual Globigerina test.

![Figure 1. Scanning electron micrograph of individual Globigerina test [1].](image)

The study area that is covered by 320 km² 3D seismic data not only contained two proven gas fields and one dry exploration well but also three remaining prospects (Prospect E, G and I) that require detail assessment in order to create mature or drillable prospects (figure 2). Uncertainties regarding reservoir properties, such as shale contents, reservoir porosity and water saturation level needs to be reduced by predict and distribute them using seismic multiattribute approach.

![Figure 2. Base map of study area.](image)

2. Methodology
Seismic multiattribute analysis is a broad term that encompasses all geostatistical methods using more than one attribute to predict some physical properties of the earth [3,4]. Schultz et al. identified three major subcategories of geostatistical multiattribute analysis techniques, which include 1) the extension of cokriging to include more than one secondary attribute to predict the primary parameter. 2) the covariance matrix to predict the parameter from a linearly weighted sum of input attributes. 3) the artificial neural networks (ANNs) or nonlinear optimization techniques to combine attributes into an estimate of the desired parameter [4,5].
The multiattribute analysis technique, which is used in this study, is limited into second category. Currently there are several methods utilized multiattribute transforms in oil and gas industry [6-8]. For this research purpose we generate pseudo well log (Gamma Ray, shale volume, total porosity, effective porosity and water saturation) from seismic internal attribute. The relationship between well log and seismic attribute is optimized using linear multivariate regression. Mathematically seismic multiattribute analysis can be traced from linear regression formulation [8]. Assuming a linear relationship between the target log and seismic attribute, a straight line can be fitted by regression:

\[ y = a + bx \]  

The optimum coefficients \( a \) and \( b \) in this equation derived by minimizing the mean-squared prediction error:

\[ E^2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - a - bx_i)^2 \]  

Refer to equation (1), if reservoir property as target will be predicted by, say, three seismic attributes at each time sample then equation will be

\[ L(t) = w_0 + w_1 A_1(t) + w_2 A_2(t) + w_3 A_3(t) \]  

where

- \( L(t) \) = target log value at sample point \( t \)
- \( w_i \) = weight value
- \( A_i(t) \) = seismic attribute at sample point \( t \)

The weights in equation (3), as the most important parameters, can be derived by mean-squared prediction error minimization process formulated as equation below

\[ E^2 = \frac{1}{N} \sum_{i=1}^{N} (L_i - w_0 - w_1 A_{1i} - w_2 A_{2i} - w_3 A_{3i})^2 \]  

Another problem that may occur during target log prediction using seismic attribute is overtraining when a large number of attributes, while always improve the fit to the training data, they may be useless or worse when applied to new data not in the training set. To overcome this problem, we need to do cross-validation process. Cross-validation consists of separating entire data set into training data set and validation data set. The training data set consists of training samples from all wells, except some specified hidden well. The validation data set consists of samples from that hidden well. The training data set is used for transformation of seismic attributes data to target log, while the validation data set is used to measure its final prediction error.

3. Results and discussions

The first attempt of seismic multiattribute analysis is predicting GR log by creating pseudo well log and distribute it as reservoir property. The generated seismic multiattribute showed that using 5 attributes and 3 points operator produced training error of 9.464 and validation error of 12.71. Pseudo GR log compared to original log has cross correlation value of 0.81.

Distributed pseudo GR on seismic cube and around T60 horizon (as target reservoir) showed that areas around well J-1 and K-1 indicate low GR value (≤ 30 gapi), characterized with red color. Low GR value means less shale or correlated with good Globigerina Limestone presence. While in H gas field low GR value only distributed near well H-1. Meanwhile, prospect G indicated with best low GR value (approximately 30 to 70 gapi) compared to prospect I and E. Prospect E showed highest GR value (≥ 120 gapi), characterized with dark color, that might indicate low Globigerina Limestone presence on that area.
Figure 3. Predicted GR overlaid with well log (left) and map of GR in T60 horizon (right).

The second attempt is generating and distributing pseudo log of shale volume (Vsh). The generated seismic multiattribute showed that using 5 attributes and 3 points operator produced training error of 11.37 and validation error of 16.23. Pseudo Vsh log have cross correlation value of 0.76 with original Vsh log.

Distributed pseudo Vsh along 3D seismic cube showed low Vsh throughout the surface of T60 horizon as shown in Figure 4. This result proved to be difficult to interpret as there was inconsistency between it and well data.

Figure 4. Predicted Vsh overlaid with well log (left) and map of Vsh in T60 horizon (right).

The third and the fourth attempt is predicting and distributing of total and effective porosity. Since data trend of both logs is similar, the end results are also similar. The predicted total porosity using 3 attributes and 5 points operator produced training error of 3.265 and validation error of 3.69, while effective porosity log prediction using 5 attributes and 5 points operators with training error of 3.54 and validation error of 4.76. Pseudo effective porosity log have cross correlation value of 0.89 with original log.
Result of horizon T60 slice along pseudo total and effective porosity cube showed similar result, with area of H & K gas field characterized with high value of porosity (≥ 50%) and area surrounding well J-1 showed low value of porosity (around 30%). From this “pseudo porosity map” Prospect E showed highest accumulation of area with high porosity (≥ 50%) while prospect I came second and prospect G only area with high porosity only limited at crest of the structure as shown in figure 5.

**Figure 5.** Predicted effective porosity overlaid with well log (left) and map of effective porosity in T60 horizon (right).

Last attempt is predicting and distributing water saturation (Sw) log. The seismic multiattribute analysis showed that 3 attributes and 9 points resulted in lowest validation error value of 18.33 with training error of 10.8. Pseudo Sw log have cross correlation value of 0.95 with original log.

Sw map generated from this analysis showed some inconsistencies where K gas field water saturation is higher (≥ 60%) than the value from the area in J-1 well vicinity (around 40%).

**Figure 6.** Predicted Sw overlaid with well log (left) and map of Sw in T60 horizon (right).
4. Conclusions
Seismic multiattribute using multivariate regression approach is a straightforward reservoir characterization technique that rely on predicting well log from seismic internal and external attribute. This process is proven simple, robust and can be utilized to quickly estimate prospective areas. However, some cautions still needed to confirm the drillable prospects. Application of seismic multiattribute on Globigerina Limestone reservoir in Madura Strait showed that the best predicted reservoir properties is porosity, whether it is total or effective, while GR came in second. Prediction of volume of shale (Vsh) and water saturation (Sw) properties proved to be difficult to interpret and showed some inconsistencies with well log data and other properties prediction results. This result is in line with previous studies regarding prediction of reservoir characteristic using seismic multiattribute [9,10]. For further research it is advisable to add external attributes such as acoustic impedance, shear impedance, Vp/Vs ratio etc.

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