Geocomputation of Monte Carlo Simulation for hydrocarbon reserves estimation, case study offshore Kalimantan, Indonesia

R A Sagoro, Supriyanto and Haryono

Geoscience Study Program, Faculty of Mathematics and Natural Sciences (FMIPA), Universitas Indonesia, Depok 16424, Indonesia

Corresponding author’s email: supriyanto@sci.ui.ac.id

Abstract. Uncertainty in geological and geophysical data affects the estimation of hydrocarbon reserves. To reduce the uncertainty, risk analysis can be performed, one of which by using Monte Carlo simulation. The purpose of this study is to estimate the volumetric reserves of petroleum using the Monte Carlo simulation. This research was conducted in the case of offshore in Kalimantan, Indonesia. There are two stages in this study, first analysing the reservoir zones to obtain rock property values used for estimation of reserves, second is calculating the probabilities by simulating random values based on their distribution and estimating hydrocarbon reserves based on these probability calculations. In addition, both stages need to be carried out as a basis for making effective decisions on the drill prospects.

Keywords: Monte Carlo, hydrocarbon, geocomputation, risk analysis, offshore

1. Introduction

Hydrocarbon exploration certainly has risks and uncertainties. The data taken at the time of acquisition such as seismic data and well data are then analysed using petrophysical analysis to produce reservoir properties [1] such as volume, porosity, and water saturation which have different uncertainties in each case due to the limited set of data available, so affecting the level of uncertainty in the calculation of hydrocarbon reserves during exploration [2].

The problem of high uncertainty in volumetric reserve calculations during the exploration can be overcome by conducting a risk analysis method [3, 4]. One way to use this method is by a simulation technique. This technique works by analysing the likelihood of large by making a description of risk and uncertainty in a form of probability distribution [5]. To be able to analyse these risks, it is necessary to do a simulation using Monte Carlo simulation or it can also be called the Monte Carlo method [6].

Monte Carlo simulations have been carried out and have been successful in several cases of resource and reserve estimation in the oil and gas field. Research conducted by Cervantes Bravo, Savioli, and Estrada in 2017 said that the Monte Carlo method can estimate oil and gas reserves in the Talara Basin, Peru [7]. Other research on the estimation of oil and gas resources in the Nordkapp Basin, Norway using the Monte Carlo method by Joel Ben-Awuah, Spariharjaona Andriamihaja, and Abdullah Ali in 2013 [8] also succeeded in estimating the oil and gas resources in the area.
2. Materials and method

This research was initiated by entering the seismic data and well data, then well to seismic tie was carried out. When seismic data and well data were bound, picking horizons and picking faults were carried out to obtain a time structure map which was then converted to a depth structure map. From the depth structure map, the prospect volume was analysed to get the Gross Rock Volume (GRV) value.

This research used Root Mean Square (RMS) attribute and Sweetness attribute to map the hydrocarbon indication directly by measuring the reflectivity in this field. RMS amplitude is the square root of the average of the squares of a series of measurements. Physically, the overall amplitude of a signal was analysed by RMS. It means that RMS can deliver the average signal amplitude. Sweetness attribute is the instantaneous amplitude divided by the square root of the instantaneous frequency. The value of the sweetness attribute will be high if an area has higher amplitude and lower frequency, while the value will be low if it has lower amplitude and higher frequency. The sweetness attribute is mostly used to identify “sweet spots” which are related to hydrocarbon presence, indicating by high value of the sweetness attribute [9].

Geocomputation of Monte Carlo simulation for hydrocarbon reserves estimation, case study offshore Kalimantan, Indonesia. Furthermore, well analysis was performed from well data to produce porosity, water saturation (SW), net to gross (NTG) values. After the required data was collected, a Monte Carlo Simulation was performed. After GRV, NTG, porosity, water saturation, formation factor, and recovery factor data were entered, then the distribution type of each variable and the number of iterations were determined. Then, calculated the probability by simulating a random value based on its distribution. After that, calculated the estimated resources and hydrocarbon reserves.

3. Results and discussion

This high RMS and Sweetness value shows hydrocarbon indication. In figure 1b and figure 1c is a map of the distribution of RMS and sweetness amplitudes in Offshore Kalimantan. The yellow lines on the map show the boundaries of P10, P50, and P90. At the P10 limit (short dashed lines) there are indications of hydrocarbons based on relatively high RMS amplitudes, but at the edges are less visible because of relatively low RMS and sweetness amplitudes. Then, at P50 (long dotted line), it is seen that the indication of hydrocarbon concentration is higher because the ratio of the relatively high RMS amplitude area is higher. Furthermore, on P90 (yellow line without breaking) almost all of them show indications of hydrocarbons in the area.

3.1. Geological model

The research area is located in Mentawir Formation and Gelingseh Formation which is dominated by massive sand and intercalation of shale, clay, and coal. Based on the RMS attribute map (figure 1b) and sweetness (figure 1c), the depositional environment in this area is a deltaic area with sediment supply from the northwest which is marked by a green arrow.

3.2. Determination of the prospect area reservoir volume

From the results of the analysis on Well X (figure 2), there is a Gas Water Contact at a depth of -4908 ft. Then, the depth is used as a base on the calculation of reservoir volume. Then, on the depth structure map (figure 1a), based on the root mean square attribute (figure 1b) there is an indication of the gas at a depth above -4500 ft. which can be used as a top reservoir. Based on these indications, the Gross Rock Volume calculation of the depth structure map in sequence P90, P50, and P10 are -4500 ft, -4704 ft, and -4908 ft, respectively.

3.3. Determination of net to gross value

Net to gross is the total net pay divided by the total thickness of the reservoir interval. Based on the X well log data (figure 3), it is found that there is an indication of a reservoir characterised by a low gamma ray log value on TVD -4892 ft to -5024 ft, so that it is associated with a sandstone reservoir.
Figure 1. (a) Depth structure map, (b) root mean square attribute, and (c) sweetness attribute of offshore Kalimantan.

There is a gas-water contact on the TVD -4908 ft, which shows that the SW value increases significantly closer to number one, so that a 16 ft net pay is obtained which is marked with a red transparent rectangle in figure 3. Therefore, the Net to Gross value for this prospect is 0.4 for P90, then 0.65 for P50, and 0.9 for P10.

3.4. Determination of porosity values

Based on the data from well X, where the prospect area is -4977 ft deep, up to -4990 ft, the porosity value has a relatively downward trend. From the observed data, in well X the mean values of P90, P50, and P10 are 0.23, 0.27, 0.32, respectively (figure 4a). Then, in the Y well data, the trend contained in the well data tends to increase deeper. Using the middle values, therefore, the values of P90, P50, and P10 at well Y are 0.21, 0.268, and 0.31, respectively (figure 4b).
The final porosity value is taken from the average value of each element in well X and well Y. The final values of P90, P50, and P10 of porosity in this study were 0.22, 0.269 and 0.315.

Figure 2. Geological model of the study area. The green arrow represented as the direction of sediment supply.

Figure 3. Well X wireline log.
3.5. **Determination of water saturation values (SW)**

Based on data from well X, at a depth of -4977 ft to -4990 ft (figure 5), a water saturation value trend that is relatively rising increasingly deep. As for quantitatively, the mean values of P90, P50, and P10 are 0.43, 0.335, and 0.275, respectively. At reservoir X well, hydrocarbons are not visible, but the reservoir is filled with water, so only the water saturation data at reservoir X is used as the final value.

3.6. **Reserve calculations with deterministic**

The reservoir reserve calculation deterministically is carried out by direct calculation. The final result of this calculation is 533.94 bcf (most likely).

3.7. **Reserve calculations with Monte Carlo simulation**

In determining the economic prospects of a good reserve calculation is needed. Integration of structural interpretation, root mean square attribute to determine hydrocarbon indications, and quantitative analysis results in lateral distribution as a consideration in determining anticline volume. The input parameters for the Monte Carlo simulation calculations are shown in table 1.
The results of statistical simulations using Monte Carlo simulation with an iteration of 20,000 show that reservoir reserves at mode is 349.16 bcf (figure 6 and figure 7) with a risk of around 23% (figure 8).

**Table 1. Input parameter calculation.**

| Input                  | Low/P90     | Most Likely/P50 | High/P10   | Distribution |
|------------------------|-------------|-----------------|------------|--------------|
| GRV (m$^3$)            | 64783848    | 518203956       | 1569251680 | Triangular   |
| NTG (frac)             | 0.4         | 0.65            | 0.9        | Triangular   |
| Porosity (frac)        | 0.22        | 0.27            | 0.32       | Beta-PERT    |
| 1-Sw (frac)            | 0.57        | 0.665           | 0.725      | Beta-PERT    |
| 1/Bg (scf/ft$^3$)      | 200         | 250             | 300        | Triangular   |
| Reserve direct calculation (bcf) | 22.95 | 533.94 | 3471.35 |             |

**Figure 6.** (a) GRV and (b) NTG with triangular distribution; (c) porosity and (d) 1-Sw with Beta-PERT distribution; and (e) 1/Bg with triangular distribution.
In figure 9, it can be seen that the GRV value is the variable that has the most impact on the simulation results because it has the greatest variance, followed by NTG and porosity variables.

![Figure 7. Result and probability density function curve with gas volume.](image1)

![Figure 8. Risk curve with gas volume.](image2)

![Figure 9. Sensitivity analysis tornado chart.](image3)
4. Conclusion

The sandstone reservoir has a bulk density (RHOB) of 2.1 gr/mL to 2.35 gr/mL, an effective porosity (PHIE) of around 27 %, and a water saturation (SW) value of around 33% which indicates a gas hydrocarbon. The Root Mean Square (RMS) attribute can detect the presence of hydrocarbons in a sandstone reservoir which is indicated by a relatively high value, then the sweetness attribute is sensitive to the presence of gas hydrocarbons which are indicated by a high sweetness value. Based on the attributes of RMS and Sweetness, the distribution of gaseous hydrocarbons is concentrated in the anticline structure.

Monte Carlo simulation can provide an estimation of hydrocarbon reserves and their risk value based on the integration of the RMS attribute, sweetness attribute, and the parameters of Gross Rock Volume, Net to Gross, Porosity, Water Saturation, and Formation Volume Factor (Bg). The comparison between deterministic (533.94 bcf) and probabilistic (349.16 bcf) yields a more convincing calculation.

Acknowledgments

Author would like to thank Dr. Eng. Supriyanto, M.Sc. and Haryono, S.Si., M.Si. for giving me the wonderful opportunity to complete my thesis under their supervision, it is truly an honour. Thank you for all the advice, ideas, moral support and patience in guiding me through this project. This project was supported by the PUTI Saintekes 2020 research programme under the Universitas Indonesia grant agreement No NKB-4917/UN2.RST/HKP.05.00/2020.

References

[1] Hartmann D J and Beaumont E A 1999 Predicting reservoir system quality and performance Treatise of Petroleum Geology Handbook of Petroleum Geology: Exploring for Oil and Gas Traps ed E A Beaumont and N H Foster (Tulsa, Oklahoma: The AAPG, USA) DOI https://doi.org/10.1306/TrHbk624C9
[2] Kok M V, Kaya E and Akin S 2006 Energy Sources, Part B. 1 207-11
[3] Aven T, Baraldi P, Flage R and Zio E 2013 Uncertainty in Risk Assessment: The Representation and Treatment of Uncertainties by Probabilistic and Non-Probabilistic Methods (New Jersey: John Wiley & Sons, USA)
[4] Lerche I 1996 Energy Exploration & Exploitation 14 503-5
[5] Mun J 2006 Modeling Risk: Applying Monte Carlo Simulation, Real Options Analysis, Forecasting, and Optimization Techniques (New Jersey: John Wiley & Sons, USA).
[6] Ben-Awuah J, Andriamihaja S and Ali A 2013 Int. J. Pet. Geosci. Eng. 1 326-42
[7] Cunha Jr. A, Nasser R, Sampaio R, Lopes H and Breitman K 2014 Computer Physics Communications 185 1355-63
[8] Cervantes Bravo R J, Savioli G and Estrada J 2017 Hybrid Method with a Probabilistic Approach to Estimate Reserves in Mature Fields Paper Presented at the SPE Latin America and Caribbean Petroleum Engineering Conference, Buenos Aires, Argentina (Buenos Aires) DOI https://doi.org/10.2118/185573-MS.
[9] Radovich B J and Oliveros R B 1998 The Leading Edge 17 1177-328