Pore Pressure Prediction Using Eaton and Neural Network Method in Carbonate Field “X” Based on Seismic Data

P S Hutomo¹, M S Rosid¹*, M W Haidar²
¹Department of Physics, FMIPA, Universitas Indonesia, Depok, Indonesia, 16424.
²Pertamina Hulu Energi, Arkadia Tower D Lt. 8, Jakarta, Indonesia

*Corresponding author: syamsu.rosid@ui.ac.id

Abstract. Abnormal pore pressure can cause some problems during the drilling process such as a blowout or sticking pipe while drilling. Pore pressure prediction may prevent the drilling hazard, especially in carbonate field that known as a complex reservoir. It is useful for mud weight determination to prevent blowout and sticking pipe while drilling. This study focuses on predicting pore pressure values and maps it through 3D seismic data. The field is carbonate reservoir which known as a heterogeneous formation with shale above the reservoir. Due to the difference of lithologies, the two different empirical parameter is used in each lithology for Eaton equation. The pore pressure prediction then correlates with the seismic attribute using a neural network method. The input parameter of the Eaton is sonic and density log. Then, the result of Eaton’s method is calibrated by leak-off test (LOT) and repeat formation test (RFT), hence the results are more accurate and verified. Then, the pore pressure is correlated to acoustic impedance, shear impedance, seismic frequency, and seismic amplitude to create a subsurface model by the neural network machine learning. The result shows that the pore pressure prediction of the model is verified by the measured pore pressure well-log data with good accuracy up to 90%. The combination method of Eaton and neural network was proven to be able to predict and map pore pressure distribution in a complex carbonate field.

Keywords: Carbonate, Eaton, neural network, pore pressure, seismic attribute.

1. Introduction
Carbonate rock is known as complex lithologies that dominating the world’s oil reserves. The field is carbonate reservoir which known as a heterogeneous formation with shale above the reservoir. The complexity of the carbonate is known because of the heterogeneous of its formation. It shows a complex relationship between porosity and permeability [1]. On the other side, carbonate rock has three pore types that may affect the pressure in carbonate [2]. Most of the abnormal pressure happens in shale lithologies. It caused by the permeability of the shale that traps the fluid flow. Consequently, it can cause some problems during the drilling process such as a blowout or sticking pipe while drilling.
Determination of pore pressure may prevent the drilling hazard, especially in carbonate field that known as a complex reservoir. Therefore, the understanding of pore pressure needed to create a drilling plan. In 1975, Eaton found a method to calculate pore pressure using an empirical parameter for many inputs [3]. It shows a good correlation because the empirical parameter can be calibrated with actual well data. This study used Eaton’s method to determine pore pressure in carbonate field. It used log data as an input parameter. The result then calibrated by leak-off test (LOT) and repeat formation test (RFT) from log data. It makes the result more accurate and verified. Heterogeneity in carbonate needs statistical approximation to use in this field. One of the statistical learning methods is a neural network. The method is used because it has a learning method to see a correlation between random trend as input data with the target data. The successes of this method are based on the algorithm and the learning method between train and test data [4]. The combination of Eaton’s method and neural network was proven to be able to create pore pressure distribution in a carbonate field. The result then can be used as a decision support data.

2. Method
This method used to create pore pressure model in carbonate field. The model is governed by using well data that is correlated with seismic data. The correlation is developed from machine learning with neural network based in general, Eaton’s method applies different normal compaction with actual pressure in the subsurface [3]. This method uses the sonic log and resistivity log data. However, this study only uses the sonic log as input data for Eaton’s method. Density log used to calculate the overburden pressure. The equation of Eaton’s method can be written as [2]:

\[
P = \frac{S}{D} - \left( \frac{S}{D} \cdot \frac{P_h}{D} \right) \left( \frac{\Delta t_n}{\Delta t_{obs}} \right)^X
\]

where
- \( P \): Calculated Pressure (psi)
- \( S \): Overburden Pressure (psi)
- \( P_h \): Hydrostatic Pressure (psi)
- \( D \): Depth (ft)
- \( \Delta t_n \): Normal sonic log (s/ft)
- \( \Delta t_{obs} \): Observed sonic log (s/ft)
- \( X \): Empirical parameter

The result of Eaton’s method then calibrated with RFT and LOT by determining the empirical parameter \( X \).

Machine learning is a method of data analysis that artificial intelligent based. It used algorithms that learn from input data. The input data are trained to get the output. In this study, the seismic attribute of acoustic impedance, shear impedance, seismic frequency, and seismic amplitude are used as an input in the neural network. Those data are used to distribute pore pressure from the well into the seismic data. In this method, we used three layers of neural network to iterate input into the output. It used twenty neurons in every layer. This study is implemented backpropagation and Levenberg - Marquard as a learning method to train input data from well and seismic. The result of pore pressure in carbonate is verified by others well.

3. Result and Discussion

3.1. Pore pressure of well data
This study used two different density to calculate the overburden pressure. The result of overburden pressure shows shifting when comes into the carbonate. It is a common condition because the density
of carbonate is more than shale. The result of overburden pressure then calibrated by LOT to get a better-verified result. In this study, to determine hydrostatic pressure used 0.4333 psi/ft, it is the constant value of fresh water based on Fertl [5]. The result of Eaton’s method is calibrated by RFT and mud weight that used while drilling. It shows an overpressure condition in shale formation of well “X2”. It is a common condition in shale formation since the shale has low permeability. The result of pore pressure in well data shown in Figure 1. This result then used as train and test data to create a model by a neural network. The train data and test data are the averages of the pressure in every 80 ft. The empirical values used in this study is 1 for shale formation, and 0.1 for carbonate formation. It values are the result of calibrated pressure by the RFT and mud weight.

![Figure 1](image1.png)

**Figure 1.** Pore pressure prediction in (a) well "X1" (b) well "X2"

### 3.2 The result of the neural network

In this study, seismic inversion used to get acoustic impedance and shear impedance. It used for the input to the neural network. The result of the inversion shown in Figure 2 that no anomaly in the abnormal pressure zone. Therefore, we can say that the acoustic impedance and shear impedance is good to use in separating the lithologies. Also, this figure showed a transition zone before the limestone zone. However, the seismic attribute of frequency and amplitude show an anomaly in an abnormal zone (Figure 3). The anomaly is shown by decreasing the amplitude and frequency in the abnormal pressure zone. It is because of the abnormal pressure causes weaker grain contact than normal pressure. Therefore, it will cause a higher attenuation that makes the attribute of seismic and amplitude lower [6].

The result of trained data using neural network shows a good correlation with the actual data in well “X1”. Those data then tested in well “X2” for the carbonate lithology. The result between actual data with test data shows a good correlation of about 92.51%. The accuracy in this result is based on the gradient between actual data as an x coordinate and predicted data as a y coordinate. This result shows in Figure 4a with RMSE of 27.8417 psi and R$^2$ of 0.6999. The qualitative result is also shown in Figure 4b that the tested data is always less than the measured data but the trend line is almost the same. Based on its result, we can see that neural network with three layer and 20 neurons in every layer. It can be
used to create a model of pore pressure in carbonate field. Therefore, the method can be used to create a model of pore pressure as shown in Figure 5.

The result of the pore pressure model shown in Figure 5 shows a good correlation compare to well data shown in Figure 6 and Figure 7. Hence these results show in psi, the abnormal pressure may be known to find the anomaly pressure that compares with nearby pressure. This result also shows a good correlation with the inversion model of acoustic impedance and shear impedance. This result shows that the model fits with the trend line on the inversion model.

Figure 2. The result of (a) acoustic impedance, (b) shear impedance.

Figure 3. Anomaly shown in (a) seismic amplitude and (b) seismic frequency.
Figure 4. Actual pressure versus tested pressure using a neural network shown in (a) quantitative data and (b) qualitative data.

Figure 5. Model of pore pressure prediction using a neural network.
6

Figure 6. Correlation between well "X1" with pore pressure model.

Figure 7. Correlation between well "X2" with pore pressure model.

4. Conclusion
From this study, we can conclude that Eaton’s method is able to determine the pore pressure by using sonic and density log with RFT and mud weight as a calibrator. Also, the attribute of seismic amplitude, seismic frequency, acoustic impedance, and shear impedance can be used as parameters to create a model using a neural network. As the result shows good accuracy, the neural network can be used to generate a model in carbonate field “X”.

Acknowledgments
We would like to thank PT. Pertamina – PetroChina East Java for permission to use the data in this study. We would like to also thank M Reza Fauzi for his permission for using his seismic inversion data as a parameter in this study. Also thanks to DRPM Universitas Indonesia for financial support of PITTA 2019 grant.
References
[1] Sayers, C., and Latimer, R. (2008). An introduction to this special section: Carbonates. *The Leading Edge, 27*(8), 1010–1011.
[2] Xu, S., and Payne, M. A. (2009). Modeling elastic properties in carbonate rocks. *The Leading Edge, January* (January), 66 – 74
[3] Eaton, B. A. (1975). The Equation for Geopressure Prediction from Well Logs. *Fall Meeting of the Society of Petroleum Engineers of AIME*.
[4] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and Machine Learning forecasting methods: Concerns and ways forward. *PloS one, 13*(3).
[5] Fertl, W. H. (1976). Developments in Petroleum Science 2: Abnormal formation pressures. Igrass 2014.
[6] Nowick, A. S., Berry, B. S., and Katz, J. L. (1975). Anelastic Relaxation in Crystalline Solids. *Journal of Applied Mechanics, 42*(3), 750.