The integration of elastic wave properties and machine learning for the distribution of petrophysical properties in reservoir modeling

T C Ratnam¹, D P Ghosh¹ and B M Negash²
¹Petroleum Geoscience Department, Universiti Teknologi PETRONAS, Malaysia
²Petroleum Engineering Department, Universiti Teknologi PETRONAS, Malaysia

E-mail: teresaclare.ratnam@gmail.com

Abstract. Conventional reservoir modeling employs variograms to predict the spatial distribution of petrophysical properties. This study aims to improve property distribution by incorporating elastic wave properties. In this study, elastic wave properties obtained from seismic inversion are used as input for an artificial neural network to predict neutron porosity in between well locations. The method employed in this study is supervised learning based on available well logs. This method converts every seismic trace into a pseudo-well log, hence reducing the uncertainty between well locations. By incorporating the seismic response, the reliance on geostatistical methods such as variograms for the distribution of petrophysical properties is reduced drastically. The results of the artificial neural network show good correlation with the neutron porosity log which gives confidence for spatial prediction in areas where well logs are not available.

1. Introduction
Reservoir modeling is an inherent part of the field development process. It integrates various disciplines such as petroleum geoscience, reservoir engineering and petrophysics. The aim of a reservoir model is to mimic the subsurface performance to the best of our knowledge. Conventional reservoir modeling employs various geostatistical methods to predict the spatial distribution of facies and reservoir properties in between wells. The model is correct at well location, however elsewhere the variograms may not depict the true geological subsurface. The uncertainty is then carried forward in the following procedure of reservoir simulation. This study aims to use elastic wave properties, aided by an artificial neural network, to derive a geologically constrained static reservoir model.

2. Literature Review
2.1. Reservoir Modeling
One of the important steps in the life of a field is reservoir modeling. It is a platform for the assimilation of available data and geology [1]. The conventional method of constructing a geological model combines various sources of data such as well logs, seismic data, rock physics and petrophysical data. Well log data is a good source of geological data which possesses the vertical resolution for reservoir simulation [2]. The issue of the conventional method arises due to the lack of data of rock and fluid properties in between the wells. Therefore, an array of geostatistical tools are incorporated to populate the grid cells.
Geostatistics is based on stochastic optimal linear estimation [3]. In static reservoir modeling, geostatistical methods are used to distribute properties such as lithology, permeability and porosity. Variogram analysis and kriging are examples of geostatistical tools [4]. Due to the limited number of wells in a reservoir, several realizations are made through stochastic simulation which relies on a vertical proportions curve established from well logs [5]. This means that the proportions of lithology which is seen at well locations are assumed to be representative of the rest of the field. Conventional geostatistical reservoir modeling methods are incapable of portraying reservoir heterogeneity that represents geological processes in temporal sequence [6].

2.2. Elastic Wave Properties
The main factors that play a role in determining the velocity of P-wave ($V_p$) and S-wave ($V_s$) are density, $\rho$, and structural strength. Apart from that, the effect of lithology also affects the velocities. Hence, seismic velocities obtained from sonic logs can be used to discriminate between sand and shale. The ratio of $V_p/V_s$ is often used to distinguish between rock and sediment types as it is usually more sensitive than just $V_p$ alone. Furthermore, changes in porosity and fluid saturation are also reflected in the seismic velocities.

2.3 Scaled Inverse Quality Factor
New seismic attributes called the scaled inverse quality factor of P-wave (SQ$^{-1}_p$) and scaled inverse quality factor of S-wave (SQ$^{-1}_s$) were developed by Hermana et al. [7] for the separation of lithology and pore fluids. The response of SQ$^{-1}_p$ is similar to the gamma-ray log whereas SQ$^{-1}_s$ is similar to the resistivity log. These attributes are formulated from the Quality Factor of P-wave and S-wave. Eq. 1 and Eq. 2 show the definition of SQ$^{-1}_p$ and SQ$^{-1}_s$ respectively.

$$SQ_p^{-1} = \frac{51}{6\rho} \frac{(M/G)^2}{(M/G-1)}$$

$$SQ_s^{-1} = \frac{10}{3\rho} \frac{(M/G)}{(3M/G)^2}$$

where $M$ and $G$ are the compressional and shear modulus respectively, and $(M/G)$ can be approximated with $(V_p/V_s)^2$. Therefore, the variables in the equations are the P-wave velocity ($V_p$), S-wave velocity ($V_s$) and density ($\rho$) which are obtained from seismic inversion.

2.4. Artificial Neural Network (ANN)
An artificial neural network (ANN) is similar to the complex network of neurons in a brain whereby it is connected by multiple processors called nodes, each producing a sequence of real-valued activations [8]. The first neuron, which is the input neuron, is triggered by data collected from the environment. The consecutive neurons, on the other hand, are activated by weighted connections of preceding neurons. ANNs are applied in various situations including regression analysis, classification or pattern recognition, data processing and forecasting time series [9].

3. Methodology
The workflow of this study aims to predict the petrophysical properties between well locations by introducing elastic wave properties. These elastic wave properties were obtained through seismic inversion. The samples that were collected were constrained to the reservoir interval of the field. The supervised learning approach was used whereby the targets (or response) were neutron porosity and resistivity whereas the features (or predictors) were the elastic wave properties.
From the results of seismic inversion, the P-wave velocity ($V_p$), S-wave velocity ($V_s$) and density ($\rho$) were extracted. The elastic wave properties were then evaluated and processed to remove outliers and anomalies, if any. Here, the $3\sigma$ algorithm is employed to detect outliers [10]. The elastic wave properties were analyzed through feature expansion to improve the correlation with the targets. Among the expanded features is the scaled inverse quality factor of P-wave ($SQ_p^{-1}$) and scaled inverse quality factor of S-wave ($SQ_s^{-1}$).

Finally, the feature selection is shown in Eq. (3) below:

$$\text{Feature}(x) = [V_p, V_s, \rho, SQ_p^{-1}, SQ_s^{-1}, \rho*V_p, \rho*V_s, V_p/V_s]$$  (3)

4. Results & Discussion

The features obtained from seismic inversion are used as input for the neural network. The neutron porosity log is taken from a section of the wells to be used as training data in the neural network. The results of the training are shown in Figure 1. As observed, the correlation coefficient is 0.95711. Then, the neural net is tested using a section of wells that were not initially included in the training dataset. The result of the training is shown in Figure 2 where the correlation coefficient is 0.90435. This satisfactory correlation is applicable for the distribution of properties in a static reservoir model, thus reducing the need to rely solely on geostatistics between wells.

4.1. Comparison with $SQ_p^{-1}$ Attribute

The $SQ_p^{-1}$ attribute is used as a lithology identifier tool as demonstrated by Hermana. Figure 3 shows the cross-plot of neutron porosity vs. $SQ_p^{-1}$. The correlation coefficient is 0.5418. This is done with as a single attribute. The results may be improved when combined with multiple attributes.

4.2. Comparison with single and multiple attribute regression

The proposed method is compared to conventional methods that are available such as single attribute regression (Figure 4) and multiple attribute regression (Figure 5). The correlation coefficients are 0.6841 and 0.7862 respectively. The multiple attribute regression produces better results than the single attribute regression, however it is less accurate in comparison to the proposed method.
5. Conclusion
The incorporation of elastic wave properties from the seismic response improves the distribution of reservoir properties in between well locations. The use of an artificial neural network can establish a strong correlation between the features and the desired output, which is neutron porosity. This approach provides a geological reference in between well locations by converting each seismic trace into a pseudo-well log. Hence, the information that is distributed between wells conforms to the geology and not merely a statistical approach.

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