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# Investigating the dependence of shear wave velocity on petrophysical parameters

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ABSTRACT

The dependence of the shear wave velocity ($V_s$) of water-saturated reservoir rocks on petrophysical parameters was investigated. Two general regression neural network (GRNN) models were developed to predict $V_s$ of sandstones, shaly sands, and carbonate rocks as a function of the compressional velocity ($V_p$), grain density ($\rho_g$), clay content, porosity ($\phi$), permeability ($k$), and the cementation exponent ($m$) at a fixed effective stress and frequency. A set of 59 sample measurements of clean and dirty sandstones and carbonate rocks was used to train and test the GRNN models.

The first model predicts $V_s$ as a function of $\phi$, $k$, $\rho_g$, $m$, and the clay content expressed as a percentage. This GRNN model was trained using two data sets consisting of 80% and 70% of the data, respectively. The truncated portions of the data were used as blind test sets to validate the GRNN model. The analysis reveals that the porosity, clay content, grain density, permeability, and cementation exponent are essential variables for capturing the variance of the shear wave velocity. Porosity appears to be the most important variable for estimating $V_s$, and the grain density is the second most important variable. The GRNN model was able to estimate $V_s$ from both the training and the blind test data sets within an average absolute error of approximately 6%. Models from the literature that predict $V_s$ as a function of porosity and clay content appear to be specific to particular lithologies, such as sandstones or carbonates. Modeling $V_s$ by including parameters such as grain density, cementation exponent, and permeability in addition to porosity and clay content appears to capture the dominating physics that affects $V_s$. By including this comprehensive set of input parameters, we have developed a generalized model to predict the shear wave velocity $V_s$ value for all types of lithology, such as carbonates and clean and dirty siliciclastics.

A second GRNN model predicts $V_s$ as a function of only $V_p$. This model was also trained using two data sets that consisted of 80% and 70% of the data, respectively. Similar to the first model, the truncated portions of the data were used as blind test sets to validate this GRNN model. The second GRNN model was able to estimate $V_s$ as a function of $V_p$ from the training sets within an average absolute error of approximately 4% while the average absolute error was 3% for the blind test data sets. The compressional velocity alone appears to be sufficient to predict the shear wave velocity.



## 1. Introduction

The application of an acoustic signal to reservoir rocks primarily generates a compressional wave and a shear wave. The compressional wave is longitudinal (in the direction of the wellbore), and its velocity $V_p$ is usually reported by conventional sonic logs. For clean consolidated rocks that are fully saturated with water, $V_p$ is estimated by the Wyllie et al. equation (1956, 1958):

$$\frac{1}{V_p} = \frac{(1-\phi)}{V_m} + \frac{\phi}{V_f} \tag{1}$$

where

$\phi$ is the rock porosity.
$V_m$ is the compressional wave velocity of the matrix.
$V_f$ is the compressional velocity of the pore fluid.
$V_p$ is the measured compressional velocity.

In contrast, the shear wave is transversal (perpendicular to the wellbore direction). However, its velocity is not commonly reported by conventional well logs. Shear wave velocities are commonly obtained from seismic reflection measurements (Han et al., 1986). The shear wave velocity $V_s$ is an important parameter for the determination of several elastic rock properties, such as Young's modulus, Poisson's ratio, the rock compressibility factor, and Biot's coefficient (Widarsono et al., 2001). These properties are commonly used to predict wellbore stability, select mud density, determine the critical production rate that minimizes sand

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production, optimize casing design, analyze subsidence, and forecast the height, width, length, and direction of hydraulic fractures (Hudson and Harrison, 1997; Economides and Nolte, 2000). Shear wave velocity is also applied in seismic technology used for reservoir characterization. Measuring shear wave velocity in the laboratory is tedious, costly and time-consuming and requires high-quality core samples that can be difficult to obtain from fractured, weathered formations and unconsolidated rocks (Castagna et al., 1985). Current correlations that relate shear wave velocity to petrophysical properties are limited in number, lack generality, and may not be realistic because they only account for a few of the petrophysical parameters that affect $V_s$ (Castagna et al., 1985; Han et al., 1986; Eberhart-Phillips et al., 1989; Koesoemadinata and McMechan, 2001). The problem of predicting $V_s$ poses several challenges related to the effect of lithology, heterogeneity, and pore structure on the rock's elastic response. The complexity of sandstones is due to the presence of both detrital and authigenic clays, and the complexity of carbonates is due to the grain and pore heterogeneity as well as the diagenetic characteristics of these rocks. Characterizing these heterogeneities and the clay distribution of rocks is essential for developing a general model that is applicable to both sandstones and carbonates.

The objective of this study is to develop general and reliable models for predicting $V_s$ in both sandstone and carbonate rocks using petrophysical parameters that are readily obtained from routine core analysis. These parameters include porosity, clay content, grain density, the cementation exponent, and compressional velocity. These parameters are also commonly measured using several well logs. $V_p$ is readily measured using the acoustic log, and the clay volume fraction is commonly measured using the gamma ray log. Porosity is readily available from acoustic, neutron and density logs. Permeability can be estimated using correlations based on the irreducible water saturation depicted at a constant bulk volume of water and may also be estimated using NMR logs. The cementation exponent may be evaluated by combining log-porosity data and resistivity data using the Pickett plot (Bassiouni, 1994).

Because of the lack of an extensive laboratory data set that relates shear wave and compressional wave velocities to petrophysical properties, our research objective is amenable to using a general regression neural network. This study is motivated by the important applications of $V_s$ data in conjunction with easily measured $V_p$ data for predicting important mechanical properties of rock, such as Young's modulus, bulk modulus, Poisson's ratio, and Biot's coefficient. The use of shear wave velocities also provides a basis for estimating petrophysical information from seismic data using, for instance, explicit inversion by amplitude variation with offset (AVO) analysis (Castagna and Swan, 1997). Furthermore, other petroleum engineering problems, such as subsidence, become easier to analyze when the shear wave velocity is known.

A few studies presented recently have proved the superiority of artificial intelligence modeling over empirical and statistical models for predicting the shear velocity from well log data. Bagheripour et al., (2015) developed a support regression vector algorithm based on the statistical learning theory to predict the shear wave velocity using conventional well log data like compressional wave interval transit time, neutron porosity, bulk density, and resistivity. Nourafkan and Ilkhchi (2015) introduced a hybrid ant colony-fuzzy inference algorithm for predicting the shear velocity using compressional wave velocity, neutron log porosity and bulk density log data. Rezaee et al. (2007) developed a back-propagation neural network model to predict the shear wave velocity using sonic log interval transit time, bulk density log, gamma ray, induction deep-resistivity log, and neutron porosity log. Rajabi et al. (2010) developed fuzzy logic genetic algorithms for predicting the shear wave velocity also from conventional well log data like latero-log-deep resistivity, bulk density log, and the neutron porosity log. Several other researchers established empirical correlations to estimate the shear wave velocity (Castagna et al., 1985; Eskandari et al., 2004; Eberhart-Phillips et al., 1989; Koesoemadinata and McMechan, 2001; Han et al., 1986). The limitation and range of application of these models is discussed next.

Castagna et al. (1985) collected $V_p$ (km/s) data from sonic logs and provided the following correlation for the shear wave velocity (km/sec) of water-saturated carbonate samples:

$$V_s = -0.05509V_p^2 + 1.0168V_p - 1.0305 \quad (2)$$

Eskandari et al. (2004) introduced the following correlation for $V_s$ for carbonate rocks:

$$V_s = -0.1236V_p^2 + 1.6126V_p - 2.3057 \quad (3)$$

Eskandari et al. (2004) reported a better fit to their data (coefficient of determination = 0.94) than the Castagna et al. (1985) correlation. Both $V_s$ and $V_p$ in the models presented above are in km/s. However, the models presented by (Eqs. (2) and 3) both lack generality because they are applicable only to carbonate rocks.

Eberhart-Phillips et al. (1989) applied multivariate regression analysis to data from samples of medium to high permeability sandstones that were fully saturated with water, in order to correlate $V_s$ and $V_p$ to porosity, clay content and effective pressure. Their correlation for $V_s$ (in km/s) is given by:

$$V_s = 3.7 - 4.94\phi - 1.57\sqrt{C} + 0.361\left(P_e - e^{-16.7P_e}\right) \quad (4)$$

where

$\phi$ is the porosity (a fraction).

C is the clay volume fraction.

$P_e$ is the effective stress (kbar).

Koesoemadinata and McMechan (2001) used well log data in conjunction with laboratory-measured data from 18 published sandstone datasets to develop correlations for $V_s$ and $V_p$. The independent variables of their correlations include effective stress, porosity, clay volume fraction, water saturation, permeability, and frequency. The general form of their $V_s$ correlation (in km/sec) is given by:

$$V_s = a_1 + a_2\phi + a_3C + a_4 \ln(P_e) + a_5S_w + a_6f \quad (5)$$

where

$\phi$ is the porosity (a fraction).

C is the clay volume fraction.

$P_e$ is the effective stress (MPa).

$S_w$ is the water saturation (a fraction).

$f$ is the frequency in MHz.

$a_1$ to $a_6$ are fitting coefficients derived from regression analysis.

For the case of 100% water saturation, the fitting coefficients are $a_1=2.664$, $a_2=5.039$, $a_3=1.691$, $a_4=0.169$, $a_5=0$, and $a_6=0.368$. Koesoemadinata and McMechan (2001) reported a coefficient of determination of approximately 0.78 for their correlation at 100% water saturation.

Han et al. (1986) investigated the dependence of $V_s$ on porosity, clay content and pressure for 75 clean and shaly sandstones that were fully saturated with brine. Using linear regression, they reported the following correlation for $V_s$ in km/s at a confining pressure of 40 MPa and a pore pressure of 1 MPa:

$$V_s = 3.52 - 4.91\phi - 1.89C \quad (6)$$

In Eq. (6), C is the clay volume fraction, and $\phi$ is the porosity expressed as a fraction. Han et al., (1986) reported a high coefficient of determination of 0.96 for their correlation. Nevertheless, these relatively high regression coefficients must be validated with