AN INTELLIGENT APPROACH FOR OBTAINING TRUE RESISTIVITY (R_T) FROM ROCK ACOUSTIC DATA : A LABORATORY VERIFICATION

by
Bambang Widarsono
Fakhriyadi Saptono
Heru Atmoko

ABSTRACT

Rock true resistivity (R_t) is known as more sensitive than compressional-wave velocity (V_p), the principal output of a seismic survey, to variation in water saturation. Therefore, it would be of a great value if there were a way to predict resistivity distribution from seismic signals. This study is essentially an effort to see the possibility of predicting R_t from V_p through a pattern recognition approach. For the purpose, a series of laboratory tests were performed on some Central Sumatran clay-free sandstone samples of various porosity values and at various water saturation levels. For studying the pattern of relationship, artificial neural networks (ANNs) were applied. From the 'training' (i.e. pattern recognition) activity performed using the ANNs, it has been shown that there are patterns of relationship between V_p and R_t. In the following 'blind test', it has also been shown that the trained relationship can be used to estimate R_t reliably using other data as input. Comparisons between estimated and observed R_t data have indicated good agreement implying the success of the approach taken in the study. This has laid the foundation and justification for further application of the approach on seismic and well-log data.

I. INTRODUCTION

Current developments in reservoir characterization have shown that much attention is given to integrating results from seismic survey into the activity. The use of seismic data is now beyond the traditional exploration activities and construction of reservoir geometry. Recent advances in seismic inversion have facilitated the exploration toward extracting petrophysical properties for building reservoir simulation models (e.g. Furre and Brevik, 2000). These developments include some works that are devoted to extracting information about water saturation distribution.

In their works Widarsono et al (2000 and 2001) encountered, despite some promising results, difficulties in obtaining water saturation values from seismic data through a combination of acoustic velocity modeling using Gassmann model (Gassmann, 1951) and artificial neural network. The main factor that was considered to be the cause is the fact that acoustic velocities do not vary significantly with variation in water saturation when compared to variation in porosity. This is also clearly shown by the Gassmann model itself, as well as by laboratory experiments performed in the past (e.g. King, 1966; Gregory, 1976; Widarsono and Saptono, 1997). Therefore, even small bias caused by, say, moderate-scale heterogeneity may result in considerable error in the predicted water saturation.

Traditionally, the main source of water saturation data for the purpose of reservoir characterization and reserves estimation is resistivity logs normally run for most oil and gas wells, due to their sensitivity to variation in water saturation. Logically therefore, it would be preferable to have first resistivity distribution substracted from seismic data, rather than trying to produce water saturation data directly from seismic. It is therefore, the main objective of the works presented in this paper is to observe relations between reservoir rock acoustic velocity and resistivity. And for the first step: experiments in core laboratory with application of artificial neural network as a supporting means of pattern recognition and data prediction.

II. INFLUENCE OF WATER SATURATION: ACOUSTIC VELOCITY VS RESISTIVITY

Theoretically, variations in water saturation have their influence in varying both rock acoustic compressional wave velocity (V_p) and resistivity (R_t). The Gassmann model of acoustic velocity in elastic media has shown that

$$V_p^{\ 2} = \frac{P_d + f(K_f)}{\rho_b} \tag{1}$$

where P_d is the P-wave modulus for the rock frame (or dry rock), and $f(K_f)$ is the function of the incompressibility of the fluid in the pore spaces. The P-wave modulus for the dry rock can be expressed, in turn, by:

$$P_d = K_d + \frac{4}{3} G_d \tag{2}$$

and the function $f(K_f)$, by:

$$f(K_f) = K_f \frac{(1 - \frac{K_d}{K_m})^2}{(1 - \frac{K_f}{K_m})\phi + (K_m - K_d)\frac{K_f}{K_m^{\ 2}}} \tag{3}$$

in which K is incompressibility (or bulk modulus), G is shear modulus, and the subscript d, f, and m refer to the rock frame (or the dry rock,), fluid, and rock matrix.

For rock containing both water and hydrocarbon, the bulk density is expressed as:

$$\rho_b = \phi \cdot \rho_f + (1 - \phi)\rho_m \tag{4}$$

where:

$$\rho_f = S_w \rho_w + (1 - S_w)\rho_{hc} \tag{5}$$

and the fluid incompressibility, K_f, which is the inverse of compressibility, c_f, is given by:

$$K_f = \frac{1}{c_f} = \frac{1}{S_w c_w + (1 - S_w)c_{hc}} \tag{6}$$

where S denotes saturation, and the subscript hc refers to hydrocarbon.

Rock frame incompressibility, K_d, in Equation (3), which is the inverse of compressibility of dry rock, c_d, is related to PV compressibility, c_p, by:

$$K_d = \frac{1}{c_d} = \frac{1}{\phi \cdot c_p + c_m} \tag{7}$$

The relation between compressional wave velocity (V_p) and water saturation (S_w) is clearly shown by the Equations (1) through (7). There are two governing variables in the main Equation (1) that are influenced by

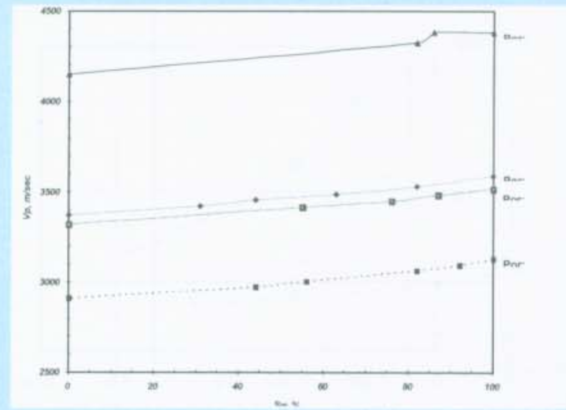

Figure 1
An example of acoustic measurement results (from Widarsono and Saptono, 2000a)

variation in S_w. Even though the two variables in the Equation (1) are reciprocal in nature but the increase in S_w tends to increase the V_p, especially in oil-water two-phase system. Figure (1) presents some experimental results on core samples.

On the other hand, the relation between R_t and S_w is more straightforward. This is true since for brine-saturated clean sedimentary rocks the total electrical conductivity is solely governed by the amount of the brine within the pore system. The electric current simply flows through the tortuous pore system that is filled continuously by the brine and completely ignores the non-conductive hydrocarbon fraction and rock matrix.

The relationship is best expressed by the empirical Archie formula

$$S_w^{\ n} = \frac{a}{\phi^m} \frac{R_w}{R_t} \tag{8}$$

where n, a, f, m, and R_w are respectively saturation exponent, twistedness degree (tortuosity) of the rock pore system, porosity, cementation factor (hardness), and brine resistivity. The Equation (8) clearly show the direct influence of variation in S_w to R_t. Figure (2) shows some experimental results using synthetic samples with various porosity

A comparison between variations in V_p and R_t reveals that variations in S_w have changed R_t much higher (up to 2,000%) than in the case of V_p (max. 20%) as later observed. This can be explained by comparing the Gassmann and Archie models in Equations (1) through (8). It is obvious that R_t is directly influenced by S_w changes (first order influence) compared to V_p that is

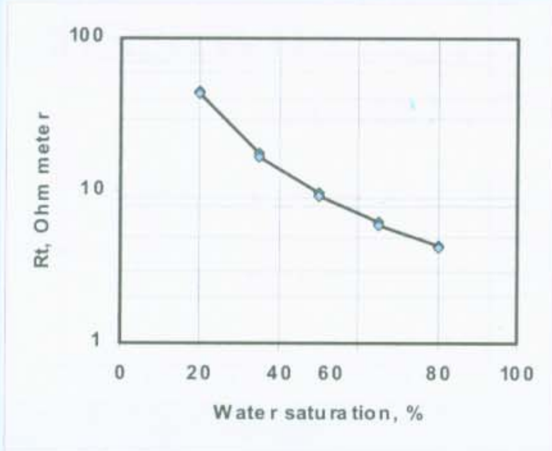

Figure 2
An example of resistivity measurement results (from Atmoko and Widarsono, 2000)

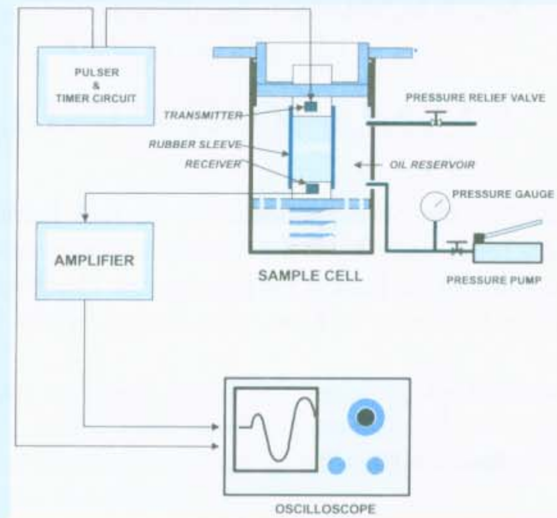

Figure 4
Acoustic velocity equipment

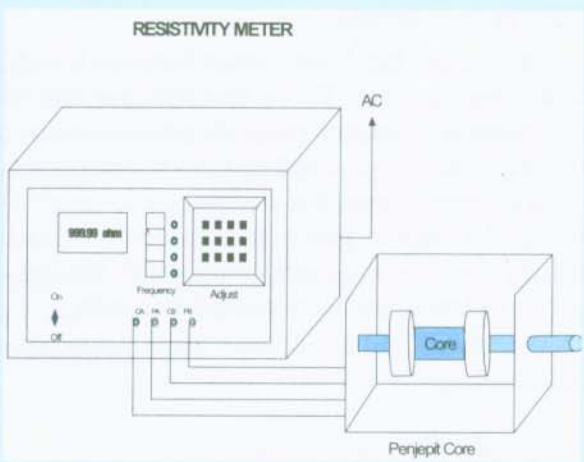

Figure 3
Resistivitymeter

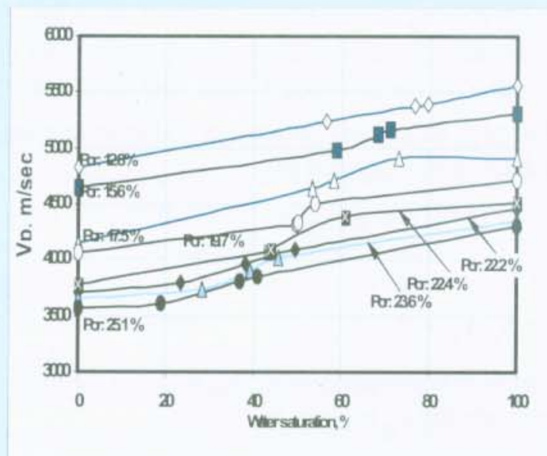

Figure 5
Measurement results for acoustic velocity measurement

influenced merely through $f(K_f)$ and r_b (second order influence).

These different degrees of response towards variations in S_w have prompted the need to recognize the relation of R_t to the traditional seismic attribute, the V_p. This is to be achieved through a series of laboratory experimental study on some sandstones.

III. LABORATORY TESTS

A series of acoustic velocity and resistivity tests were conducted on 8 samples of shale-free Central Sumatra sandstones with porosity ranging from 12.8% to 25.1%. In the tests, all dry samples were fully saturated using representative synthetic brine. No clay swelling was feared since the samples are basically clay-free.

In the fully saturated condition, as well as after some de-saturations through the use of porous plate apparatus, both V_p and R_t (see Figures (3) and (4) were measured. Figures (5) and (6) present examples of the test results. The results are in accordance with the common expectation even though the 'jump' in V_p as the S_w ap-

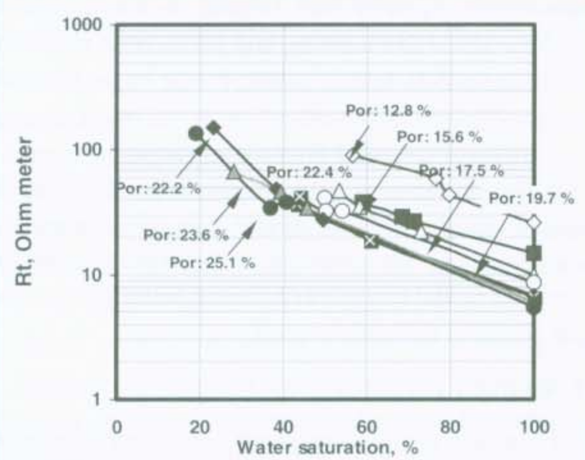

Figure 6
Measurement results for resistivity measurement

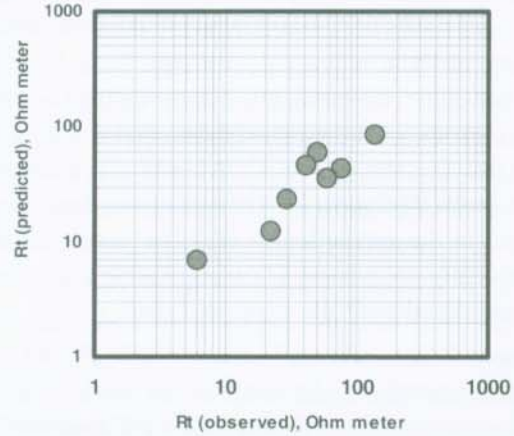

Figure 7
Comparison between predicted and observed R_t values

proached 100%, as observed by Gregory (1976), Domenico (1976) and suggested by the Gassmann model, was not encountered for an unclear reason. The use of high net overburden pressure (2,500 psi), meant to simulate the 'real' condition is probably the cause. At high external pressures, the gap in V_p between dry and fully saturated sands tend to be less than in the case of low external pressure (Fjaer, 1992).

As additional data, water saturation, porosity, bulk density, and shear wave velocity (V_s) were also measured. As the final laboratory data, a set of V_p, R_t, S_w, f, r_b, acoustic impedance (AI), and Poisson ratio (n) was available for the purpose of pattern recognition between V_p and R_t data.

IV. PATTERN RECOGNITION FOR $V_P - R_T$ RELATIONSHIP

For the purpose of finding the correlation between the V_p and R_t, artificial neural networks (ANNs) were applied to measured data. ANNs are the most popular technique in artificial intelligence for advanced signal processing. Given a set of multivariate input and target measurements, ANNs can learn and extract their complex non-linear relationships. The relationships can be applied to estimate the target variables when the actual measurements are not available. Many previous studies have shown encouraging results in field applications, compared to the well-established techniques such as multiple linear regression and discriminant analysis (e.g. Wong et al., 1995; Bruce et al., 2000).

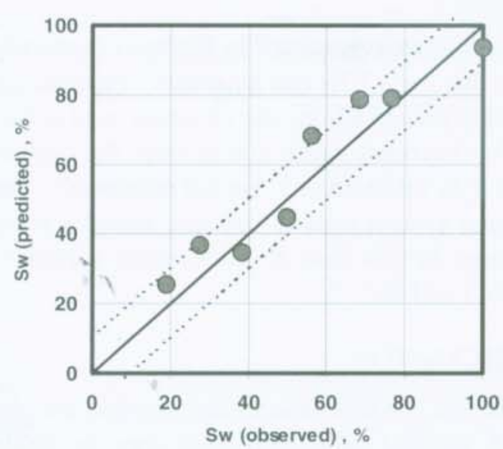

Figure 8
Comparison between predicted and observed S_w values.

The neural networks used in this study are the supervised backpropagation networks. Backpropagation is a gradient descent algorithm that uses to estimate the coefficients (neural connection strengths) by minimizing an error function. Readers can refer to Bishop (1995) for technical details.

The application of ANNs in this study is divided into two parts, 'training' and 'blind test'. In the training stage, the ANNs are trained and forced to find relationships among V_p, R_t, AI, and n. The reasons behind the use of V_p, R_t, AI, and n in the training is that those variables can usually be derived from log data, except n due to rarity in shear wave velocity data from log. In the blind test stage, the connectivity among the variables is tested on some of the measured data that is not included in the training stage. The V_p, AI, and n (variables that can theoretically be derived from seismic data) are used as input in the prediction of R_t. The predicted R_t and subsequently calculated S_w (using Archie equation) are then compared with the measured data.

From 36 data points (i.e. 36 sets of V_p, R_t, AI, and n) obtained from the eight samples, 28 were used in the training stage and the remaining 8 were assigned to the blind test. For training the ANNs, 9 hidden layers were finally used to achieve convergence between predicted and observed values at an acceptable training error of 0.00012. In the blind test stage the 'trained' ANNs was applied on the 8 data sets and the comparisons between predicted and observed R_t and S_w (calculated) were made and are presented in Figures (7) and (8). All deviations from the diagonal lines are within an acceptable range of tolerance.

Comparisons presented in Figures (7) and (8) have shown that the ANNs can reasonably recognize the relationship pattern among the variables used in the training. This becomes worth noting since the responses of V_p and R_t to variation in S_w are not necessarily similar in gas-water system used in the core samples in term of regularity. In this case, R_t shows more regularity (see Figures 5 and 6).

V. DISCUSSION

The use of Gassmann model to relate the observed V_p to S_w seemed to be impossible since the model predicts the occurrence of a 'jump' in V_p as water saturation approaches 100%. As stated earlier, this 'jump' does not occur for a probable reason also suggested earlier. This also means a difficulty if Gassmann modeling is to be applied to extract water saturation information from seismic data. Nevertheless, the success in relating V_p to R_t at laboratory scale, as concluded from this work, has laid a foundation for a real field application.

The success in the application of ANNs in the carefully measured laboratory data suggests that the same approach can be applied at field scale with log data used as training data and seismic derived attributes used as input for R_t prediction. The task of applying the approach to the field is not easy. The heterogeneity that characterizes most of rock formations can easily raise problems in ANNs training and prediction, and consequently a careful data selection has to be performed.

The choice of R_t instead of S_w as the deliverable from the approach used in this study is meant to provide flexibility to engineers and geologists in choosing the most suitable water saturation model they think suitable for their reservoirs. As commonly acknowledged, no single saturation model can suit to different heterogeneity problems found in different reservoirs.

VI. CONCLUSIONS

From the study, some main conclusions have been drawn:

1. Although different in response towards variation in water saturation, relationships between compressional wave velocity (V_p) and true resistivity (R_t) have been established by the use of artificial neural networks (ANNs), this has laid the foundation for the use of seismic data to predict the distribution of R_t.
2. The problem of difficulty in applying Gassmann model on the observed V_p (air-brine system) data resulted from the work has been minimized by the use of ANNs.
3. The use of 'trained' ANNs in the blind test has proved successful. All estimated water saturation values (calculated from the predicted R_t using Archie equation) are in good agreement with the corresponding observed values.
4. The training process of the ANNs on the training data used several assigned hidden layers before an acceptable training error was reached. The training process for field scale would be more complicated and tricky. Caution has to be taken in assigning number of hidden layers.

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