Hydrocarbon-bearing dolomite reservoir characterization: A case study from eastern Canada

Amit Kumar Ray, Ritesh Kumar Sharma and Satinder Chopra, Arcis Seismic Solutions, TGS, Calgary, Canada.*

Summary

Carbonate reservoir rocks constitute 20% of sedimentary rocks while it holds more than 50% of the world's proven hydrocarbon reserves and accounts for 40% of the world's total hydrocarbon production. Therefore, carbonate reservoirs are very important targets for oil and gas exploration. Hydrocarbons are produced where these carbonates have been fractured and dolomitized and laterally sealed by tight, undolomitized limestone. However, it is a difficult task to differentiate between limestone and dolomite. Nevertheless, a photoelectric (Pe) log curve can be used at the well location to discriminate between limestone and dolomite formations. While Pe logs exhibit almost constant values for background limestone, the dolomite units are represented by low values of Pe relative to the higher and almost constant values of background limestone. The purpose of the present work is to map the lateral extent of a dolomite reservoir unit in the area of interest in eastern Canada using a Pe volume derived from seismic.

For this study, multiattribute regression analysis and probabilistic neutral network (PNN) are used to validate and predict hydrocarbon accumulations associated with hydrothermal dolomite. The Pe property has been effectively predicted and validated throughout the 3D volume and has been found to characterize the dolomite reservoir efficiently.

Introduction

The study area is a carbonate reservoir located in eastern Canada. The reservoir encompasses hydrocarbon charged thin hydrothermal dolomite units within the thicker limestone package. The objective was to characterize the dolomite reservoir units and capture the spatial heterogeneity efficiently within the 3D area.

The latest available density logging tools make it possible to differentiate between dolomite and limestone using the photoelectric index (Pe) log. As the low-energy gamma rays are absorbed by the formation, they are recorded by Pe log in units of barns per electron (b/e). The recorded log value is directly proportional to the combined atomic number of the individual elements within the formation. The higher the average atomic number of the elements within the formation, the higher Pe value the formation exhibits. As dolomite has lower average atomic number than calcite, dolomite formation exhibits lower Pe value than limestone formation. Thus, Pe is a good tool to distinguish a dolomite formation from a limestone formation in a carbonate environment.

Neural networks have gained in popularity in geophysics over the last two decades. They have been applied successfully to a variety of geophysical problems. Among other applications, neural networks can be trained to identify the complex, non-linear relationship between petrophysical data and seismic attributes.

There are many different types of neural network implementations. The most common neural networks, that have been widely used in geophysical problems, are the multi-layer feed-forward neural network (MLFN) (Berge et al., 2002; Herrera et al., 2006) and the probabilistic neural network (PNN) (Leiphart and Hart, 2001; Hampson et al., 2001). The potential advantage with PNN is that by studying the mathematical formulation, its behavior can often be understood better than MLFN (Hampson et al., 2001).

Probabilistic neural network (PNN) derives a non-linear relationship between seismic data and its various attributes with petrophysical properties and predicts the suitable petrophysical property away from the well (Hampson et al., 2001; Leiphart and Hart, 2001). It has been reported that neural networks effectively predict petrophysical properties such as porosity, Gamma Ray, photoelectric index etc. (Chopra and Pruden, 2003; Minken and Castagna, 2003; Pramanik et al., 2004; Singh et al., 2007; Calderon and Castagna, 2007) using seismically derived attributes.

In this paper, multiattribute linear regression and PNN have been applied in a hydrothermal dolomite field to predict photoelectric log property (Pe) for characterizing the dolomite intervals. Neural networks combine high resolution well log data with laterally continuous seismic data and convert the seismic data to an appropriate and interpretable petrophysical data volume (Ronen et al., 1994; Schultz et al., 1994a, b). Relationships between various seismic attributes and available Pe curves have been established and validated through multiattribute regression and PNN. Pe curve is used to discriminate lithology, which is important in hydrothermal dolomite fields.

Method and analysis of results

An integrated workflow has been formulated to characterize the dolomite reservoir and is shown in Figure 1. As the first step, well log data was analyzed to see the correlation between the elastic and petrophysical properties and to delineate the dolomite reservoir units in well log domain. For this, crossplot analyses of well log data in the ZOI are performed. One such analysis is shown in Figure 2, a crossplot of computed P-impedance and S-impedance log curves, color-coded with Pe log curve. The anomalous and low Pe points on the crossplot space corresponding to high values of both P-impedance and S-impedance separate out from the points with relatively higher Pe values. Those anomalous points with low Pe values have been captured (red polygon) and back-projected to the well log panel. The captured zone has been interpreted as the dolomite reservoir units and can be distinguished clearly from the background limestone with relatively higher and flat Pe values. Pe has been found to be a distinctive lithology indicator in the carbonate environment that can well delineate the dolomite reservoir units. Consequently, multiattribute linear regression and PNN have been used to predict the Pe

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property from the seismic attributes for the purpose of characterizing dolomite reservoir units.

Prestack inversion has been carried out to derive P-impedance and S-impedance volumes from prestack seismic gather data. Lambda-rho and Mu-rho attributes have been computed from the inverted P-impedance and S-impedance volumes. A combination of seismic attributes that includes these inversion attributes were input to the multiattribute regression and PNN process to predict Pe property.

To see the correlation of any single seismic attribute with the Pe log, single attribute regression was performed with the P-impedance attribute. A crossplot between the inverted P-impedance and a well log Pe is shown in Figure 3. It is observed that there is considerable scatter in the crossplot space and the correlation coefficient is very low. Therefore, it would not be advisable to use single attribute regression analysis to predict Pe.

Now, multiattribute regression and PNN was performed to the data. The key aspect of this method is the selection of seismic attributes to be used in the neural network training. For this purpose, a multiattribute stepwise linear regression analysis (Hampson et al., 2001) was performed using 12 wells. The wells considered were almost uniformly distributed throughout the 3D area. The convolution operator length and optimum number of attributes were chosen using the cross-validation criteria (Hampson et al., 2001). The additional attributes always improve the correlation to the training data, but they may be useless or worse when applied to new data not in the training set. This is called overtraining (Hampson et al., 2001). In the process of cross-validation, one well at a time is excluded from the training data set and prediction error is calculated at the excluded well location. The analysis is repeated for all the wells, each time excluding a different well.

An operator length of 7 samples gave the minimum validation error with 5 attributes. The attributes were 1/(Lambda-rho), 1/(P-impedance), Sqr(Mu-rho), Instantaneous frequency and Filter of (55/60 -65/70) on seismic data. Figure 4 shows the plot of training and validation error curves versus number of attributes for the optimum operator length of 7 samples. By performing the stepwise regression and validation tests before training the PNN, the problem of overfitting the data is eliminated (Schuelke and Quirein, 1998, Hampson et al., 2001).

The relationship derived from multiattribute linear regression was then applied to the data to estimate Pe. Figure 5 shows the crossplot between predicted Pe and actual well log Pe using multiattribute linear regression. We get a correlation coefficient of 0.74 between the well log Pe and predicted Pe for the wells included in the training. It is observed that using multiattribute linear regression scattering of the data points in the crossplot has been reduced compared to the single attribute approach, but there is still some obvious scatter observed in the crossplot space.

Then, PNN was trained using the seismic derived attributes which were found to be optimum based on the multiattribute regression analysis. PNN was able to estimate Pe with a good degree of accuracy. The average training correlation at the well locations was 0.88. Moreover, the average validation correlation at the well locations was 0.61 which gave confidence about the predicted Pe volume. Figure 6 shows the crossplot between actual Pe and predicted Pe at the well locations. To show the match between actual Pe and predicted Pe they are overlain in the log view panel and shown in Figure 7. Figures 6 & 7 illustrate that actual and predicted Pe exhibit a reasonably good correlation at the well locations.

The predicted Pe volume was analyzed and a fairly good match was seen at the blind wells. Figure 8 shows a section of the predicted Pe volume passing through blind well A. A Pe map has been generated for the reservoir unit from predicted Pe volume. The map is shown in Figure 9. Low Pe zones are indicated by warm colors on the map and the wells falling within those zones have been found to be high net-to-gross dolomite wells. Therefore, the predicted Pe response within the reservoir interval correlates fairly well with the net-to-gross dolomite within the same interval throughout the 3D area.

The workflow of the adopted method is given below:

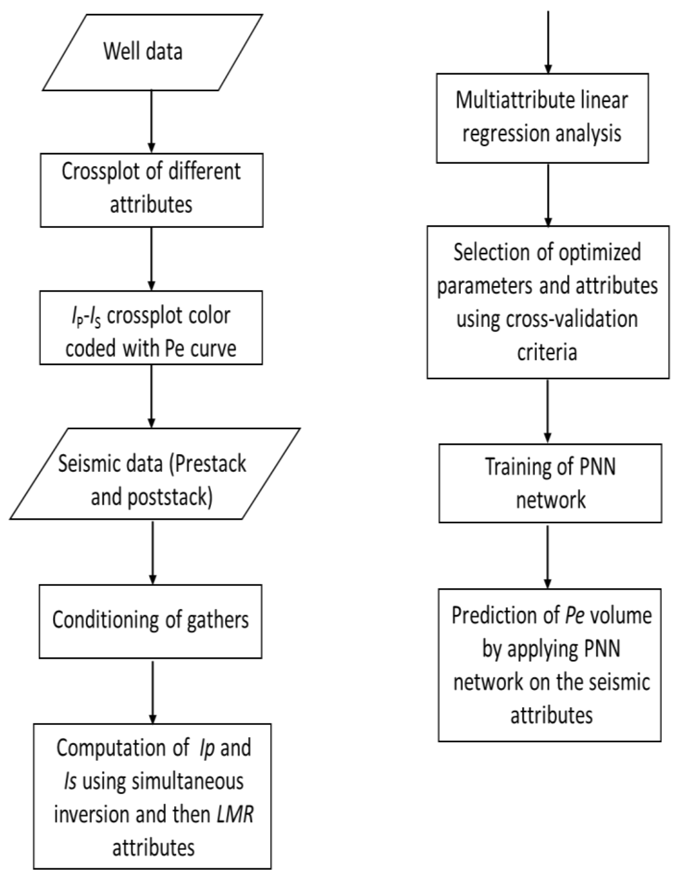

Figure 1: Integrated workflow for estimating Pe volume to characterize the dolomite reservoir

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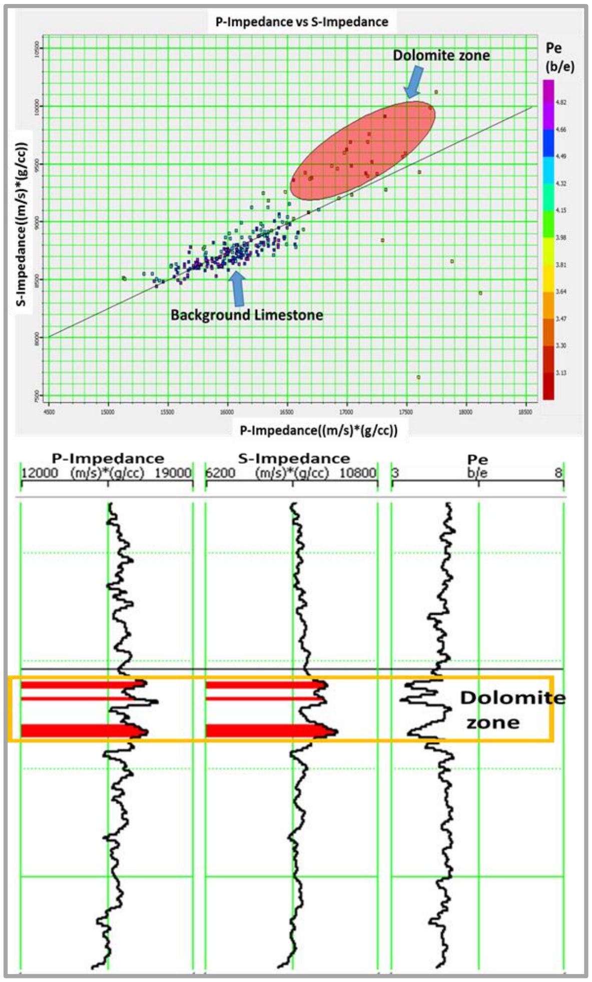

Figure 2: Crossplot of well log P-impedance and S-impedance, color coded with Pe log curve (above). Captured points enclosed by the red polygon are back projected on the well log panel (below).

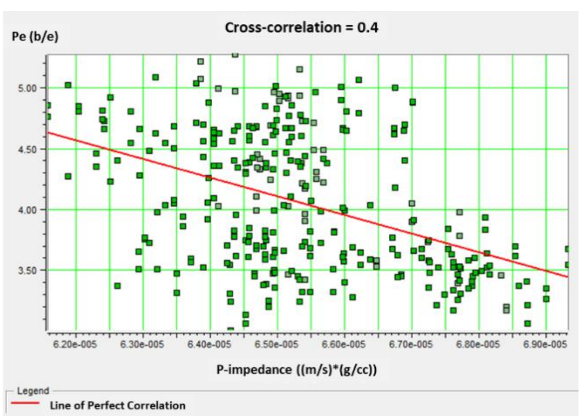

Figure 3: Crossplot of inverted P-impedance and well log Pe for 12 wells. A correlation of only 0.4 is observed between inverted P-impedance and well log Pe.

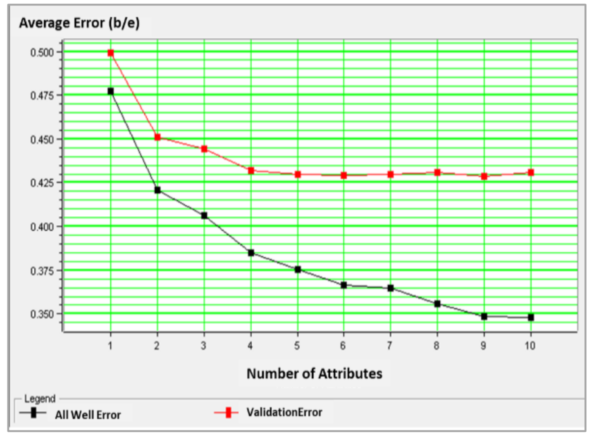

Figure 4: Average training and validation error versus number of attributes for the optimum operator length of 7 samples. Black curve represents average training error and red curve represents average validation error. The validation error does not improve after 5 attributes.

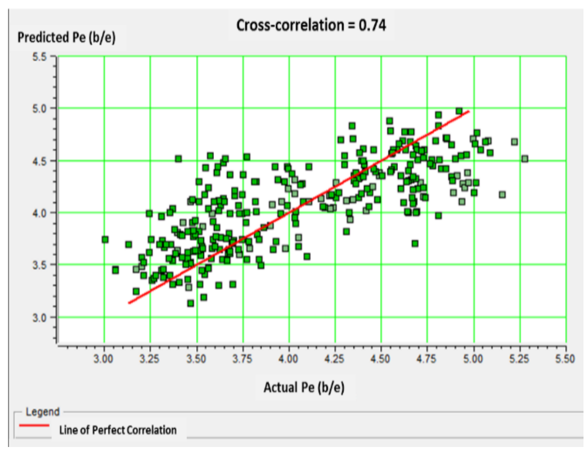

Figure 5: Crossplot of actual Pe and predicted Pe derived using multiattribute linear regression for 12 wells. A correlation of 0.74 is observed between actual and predicted Pe.

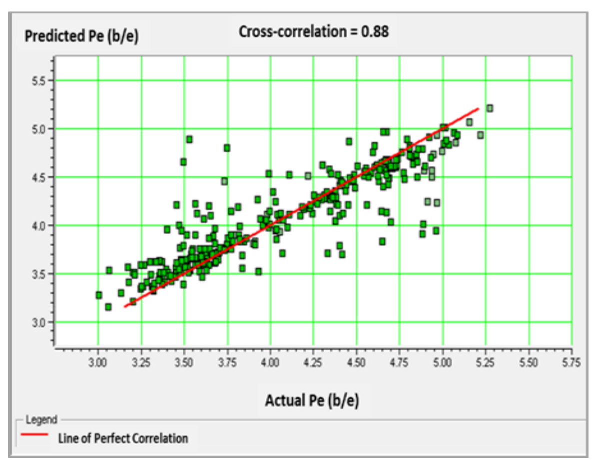

Figure 6: Crossplot of actual Pe and predicted Pe derived using PNN for 12 wells. A good correlation of 0.88 is observed between actual and predicted Pe.

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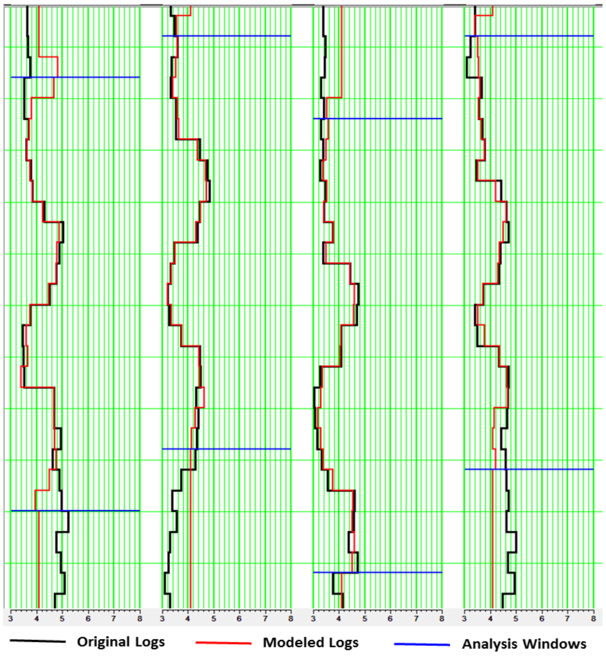

Figure 7: Log panel showing the match between actual Pe log and modeled Pe log derived using PNN for different wells.

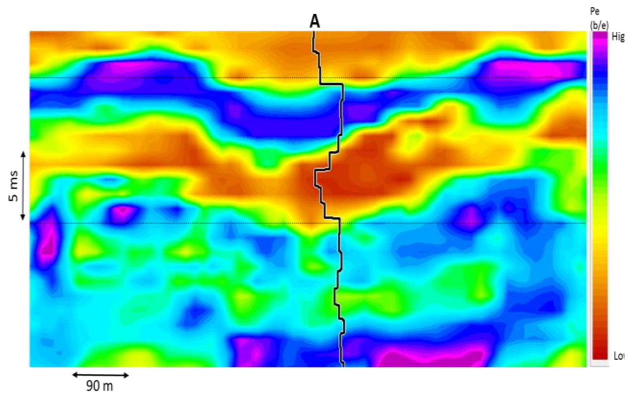

Figure 8: Segment of Pe section passing through blind well A. Pe curve is overlain on the Pe section for comparison.

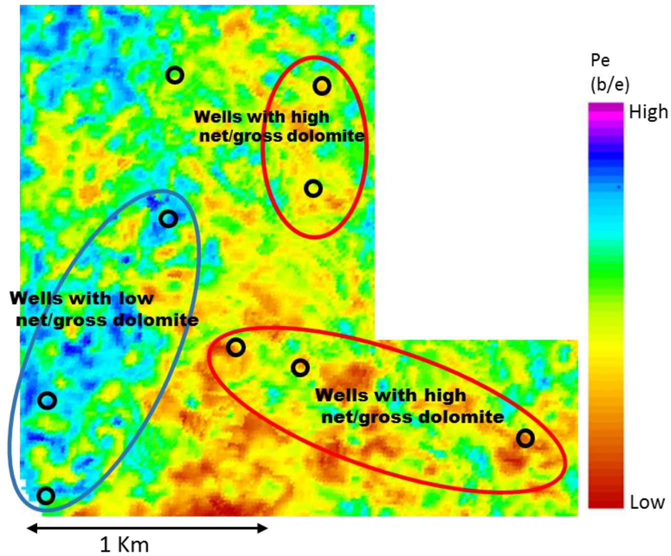

Figure 9: Map showing spatial distribution of average Pe values within the reservoir unit. Warm color represents low Pe values which is indicative of high net/gross dolomite zone.

Conclusions

Photoelectric (Pe) log curves have been found to be a distinctive lithology indicator in the carbonate environment which has delineated the dolomite reservoir units from background limestone in the area of interest well. The Pe property has been predicted using multiattribute linear regression and probabilistic neural network (PNN) using seismic and inversion-derived attributes. The predicted Pe has been validated with the Pe log curve at a blind well location and a reasonably good match has been observed. It has been found that throughout the 3D area the predicted Pe response within the reservoir interval correlates fairly well with the net-to-gross dolomite within the same interval.

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EDITED REFERENCES

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