Lithology prediction in the Taranaki Basin using neural network applications

CL Gosse[1] and BA Sissons[2]

[1] *Special Projects Geophysicist, Hampson-Russell Software, 510, 715-5 Ave SW Calgary AB T2P 2X6, Canada, Telephone 001-403-266 3225, Fax 001-403-265 6651*

[2] *Fletcher Challenge Energy, Private Bag 92-114, Auckland*

Abstract

This paper is a unique study of lithology prediction in the Taranaki Basin using neural network algorithms to enhance seismic resolution and improve reservoir modelling and production. Neural network algorithms are useful for reservoir mapping, lithology classification and porefill prediction. They have the ability to train using a combination of seismic attribute information and well data. Training refers to the process within the algorithms by which they make their optimisation. During the training process non-linear transforms are derived from the intricate relationships between seismic and well data. These transforms when applied to the seismic volume can improve its resolution for predicting target log properties. The lithologic properties of interest in this study are sand/shale discrimination, porosity and water saturation.

Geological background

The method is applied here to the Mount Messenger Formation. The Mount Messenger Formation contains fine grained turbidite fans having excellent reservoir qualities of up to 28% and 300 mD permeability and ranging in thickness from one to forty metres. Mount Messenger wells typically produce in the range of 50 to 400 bopd often with significant water cut. Log information from twenty nine wells within the study area provided an excellent training data set because they are representative of various types of reservoir quality: well developed sands, marginal producing sands, and non-producing units.

Introduction

The method requires the entry of a number of attributes derived from the seismic volume surrounding the training set of wells. Initially, the seismic volume was inverted to impedance (guided by well logs) because impedance has been found to have a very high correlation with porous sands. Several attributes were calculated in the pre-stack domain to test for AVO responses associated with producing zones: intercept, gradient, near stack and far stack. The inversion result and AVO attributes were fed into Hampson-Russell's neural network program Emerge as external attributes. Complex seismic trace attributes, for example, instantaneous frequency and amplitude envelope, were automatically calculated within the program. It has been shown that neural networks outperform conventional seismic processing techniques because they do not require any a priori model or wavelet extraction. Emerge determines an empirical relationship between seismic attributes and log data, and transforms information from the seismic attribute domain to the petrophysical domain. The algorithms use the convolutional model which uses several seismic samples for the computation of each log value (Figure 1). The neural network applications then take these extra samples and assign weights to them in order to derive a non-linear, weighted combination of multiple attributes that best predict the target rock property.

Theory

Selecting the group of attributes that best predicts the target rock property is first done through step-wise regression. This procedure identifies the optimal weighted combination of attributes that have the lowest prediction error. The best single attribute is calculated by an exhaustive search and is then removed from the list of attributes and cannot be chosen again. The second best attribute is chosen based on the lowest prediction error for the pair, and so on. Transforms of the target log and seismic trace attributes can be non-linear, but step-wise regression is a linear system and is written as follows:

$$L = w_0 + w_1*A_1 + w_2*A_2 + w_3*A_3 + ... + w_n*A_n$$

where L is the measured log value, * denotes convolution, w_i are operators derived by minimizing the mean-squared prediction error and A_i are attributes. The attributes selected by step-wise regression are then fed into multi-layer feedforward and probabilistic neural networks. The multi-layer feedforward neural network (MLFN) is described as having an input layer of nodes or attributes, one or more hidden layers, and an output layer of a single node or predicted log value (Figure 2).

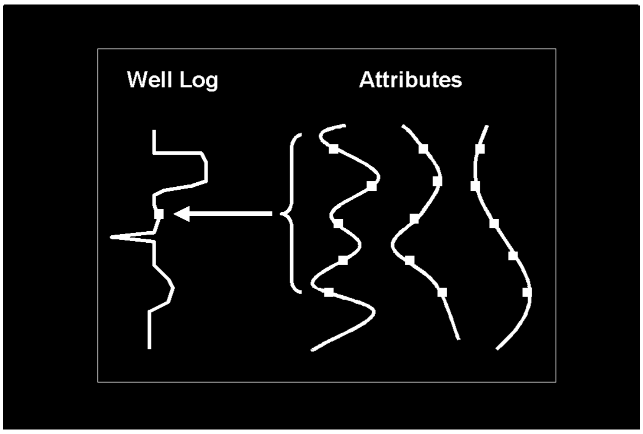

Figure 1. A five point convolutional operator correlating 15 points on several neighbouring attributes with each sample on the target log.

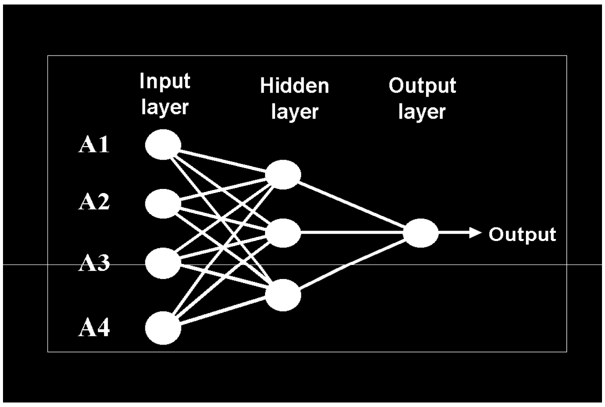

Figure 2. Three layer multi-layer feedforward network.

The nodes are connected by weights calculated by minimizing the mean-squared error between measured values and predicted values. The probabilistic neural network (PNN) is an interpolation algorithm and is analogous to geostatistical kriging, however, the distinction must be made that kriging relies on the variogram for spatial variation, whereas PNN measures distance between attributes scaled by a sigma function applied to each attribute. Sigmas are calculated by minimizing the validation error.

The transforms derived by the neural network techniques were applied to the entire seismic volume. Prediction error and uncertainty estimations were performed through a process called cross validation that determines the optimal number of attributes that when combined had the highest predictability. Theoretically, the more attributes used, the lower the prediction error. However, there is a limit to the resolution obtainable depending on the quality of the data and on the physical properties of the reservoirs. Using too many attributes may result in over-training. Cross-validation allows the transform to be evaluated for its predictive power. It removes a known value from the training set and tries to predict it based on surrounding values.

Conclusions

This is a preliminary report on an ongoing study using neural networks to predict reservoir properties in the Taranaki Basin.

References

Hampson, D., Schuelke, J., Quirein, J., 1999, Use of multi-attribute transforms to predict log properties from seismic data, submitted to Geophysics.

Masters, T., 1994, Signal and image processing with neural networks: John Wiley & Sons, Inc.

Masters, T., 1995, Advanced algorithms for neural networks: John Wiley & Sons, Inc.

Authors

BRYAN A. SISSONS is a geophysicist in the Petroleum Development group at Fletcher Challenge Energy currently working on the onshore producing fields. Previously he worked for Esso in Australia and for New Zealand Oil & Gas.

CINDY L. GOSSE joined Hampson-Russell's Calgary office in January 1998 as a Special Projects Geophysicist specialising in inversion methods, geostatistics, multi-attribute prediction and neural networks. Cindy holds a BSc (Hon) in Geophysics from Memorial University of Newfoundland and a MSc in Geophysics from the University of Calgary. She is a member of the SEG, and CSEG and also writes the 'Tracing the Industry' column in the CSEG Recorder.