Probabilistic Neural Network inversion for characterization of coalbed methane

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Summary

The seismic guided estimation of reservoir properties away from the wells is a common problem that geophysicists, geologists and reservoir engineers face every day. This problem is due to low resolution of seismic data as well as the lack of proper models that link the seismic data to the borehole data. Geostatistical methods help resolve this problem, but these methods rely only on a linear fit between seismic attributes and reservoir parameters. Artificial neural networks are the best method to relate the non-linear fit between the borehole parameters to seismic volume parameters to better understand the heterogeneity of the reservoir properties. Probabilistic neural networks (PNN) are used to invert the seismic data of coalbed methane (CBM) field from northeast Australia to better understand the reservoir properties of the coals sandwiched between sands and shales. PNN has not only helped to improve the vertical resolution but also the lateral variation in the heterogeneity of the reservoir.

Introduction

The contribution of production from the unconventional reservoirs like shale and coal is increasing everyday to the energy needs of the World. These reservoirs have low permeability often act as both the primary source rock as well as the reservoir rocks. These are not only thin but wide spread in the basin. The characterization of these reservoirs is a challenge to the geoscientists in terms of resolution and distribution in an area. The calibration of well logs (high) resolution with 3D seismic data (low resolution) is a challenge while building the comprehensive geological models.

Artificial Neural Networks (ANN) was introduced to the geosciences community in 1980's. ANNs have the ability of recognize complex, non-linear relationships between seismic attributes and petrophysical data. These relationships are applied to seismic data to predict inter-well reservoir properties. However, there is the danger that the neural network can become "over trained". That is, the fit at the wells is excellent, but the underlying model is too complex and does not lead to physically meaningful results away from the well. This problem is addressed by using the technique of cross-validation, in which we remove wells from the training stage and then 'blindly', predict these wells in the validation stage (Herrera et al., 2006). The objective of this paper is to apply probabilistic neural networks (PNN) to invert the seismic data volume to impedance by training and validating the acoustic impedance logs at the wells.

Probabilistic Neural Networks

The ability of ANNs to detect and recognize data patterns and to exploit functional, complex non-linear relationships between multiple data inputs provides for a powerful exploration tool. ANNs are robust in noisy or missing data sections that solve ambiguities or differences between data inputs. ANN results are developed through repeated training. An input model may not be required to be successfully applied.

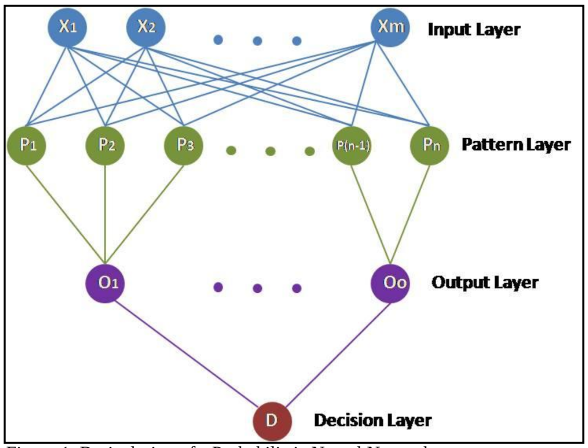

Figure-1: Basic design of a Probabilistic Neural Network

Since the 1980's many different artificial multi-layer feed-forward neural networks have been successfully applied to various geophysical problems. With good quality seismic and well log data, the PNN is favored. The PNN does not depend on an input forward model and does not require knowledge of the seismic wavelet. It has less of a 'black box' approach associated with it and tends to be more stable than the traditional multi-layer feed forward neural network (Hampson et al., 2001). A PNN is a mathematical interpolation method implemented via a 3-layered feed forward neural network architecture. Training involves only one pass through each training node. The output target log values are assumed to be a linear combination of the log values available in the training data. Figure 1 shows the basic design of a Probabilistic Neural Network.

The PNN uses Gaussian weighting functions which fit the seismic attributes to the training samples by a generalized nonlinear regression approach. The key parameter in the PNN method is the sigma factor, which controls the width of each Gaussian function. The sigma factor is allowed to vary for each input attribute (Hampson et al., 2001). The main advantages of PNNs are that is not dependent on an initial set of weights. Second, the weights are determined entirely from the data, and there is no problem with convergence to a solution. Cross validation systematically removes each well used in the training process from the training set. The multiattribute transform is recalculated with the well absent, or hidden, from the training process. The average predictive error of all the hidden wells is referred as the validation error. The validation error is the error associated with applying the PNN to the entire seismic data volume. Multiattributes, used as PNN inputs, may be geologically disconcerting; many attributes may be statistically significant but do not have theoretical explanations (Leiphart and Hart, 2001). Multiattributes must be interpreted within a geologic framework, not a statistical one. Geologically plausible and physically realistic results are necessary to be confidently used for exploration and exploitation purposes.

Example

The principles of PNN are applied on a coalbed methane reservoir to invert the seismic data to acoustic impedance volume to characterize the reservoir. This field is located in the Bowen basin, North East Australia. The Bowen basin is Permian-Triassic age major economic coal basin that extends approximately 900 km in a generally north to south direction in the eastern portion of the Queensland state of Australia. Figure 2 is a map of Australia which outlines the approximate geographical limits of the Bowen basin in Queensland. The Bowen basin is considered a marginal basin due to its location being marginal to the cratonic platform. Deep troughs in the eastern side of the basin developed because of the New England orogen thrusting and crustal thickening. These troughs were subject to high rates of subsidence in the late Permian. Toward the end of the Permian, the coal measures formed in environments described as fluvio-deltaic with fluvial elements transitioning to a paludal complex. Marginal basins in Australia tend to be characterized by a thicker sequence of coals broken into numerous coal seams and generally

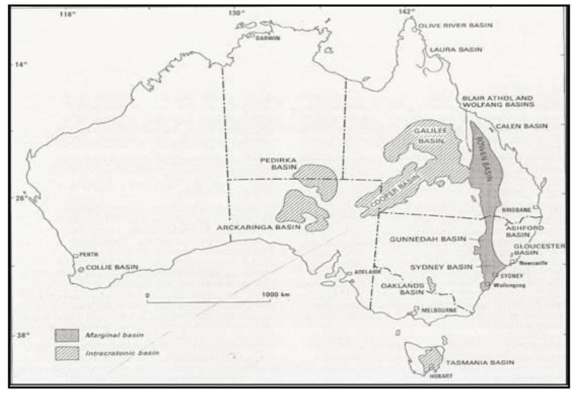

Figure-2: The geographic location of the Bowen basin in Australia (After Hunt et al., 1989)

contain a lower coal to sediment ratio than intracratonic basins (Hunt et al., 1989).

In this study, we used five wells which have seismic to well ties from the synthetic seismograms. Impedance logs were generated using the P-wave and density logs at the well locations and these logs were trained using probabilistic neural networks. An impedance model was built initially by using horizons of interest. This initial model along with amplitude envelope and amplitude weighted cosine phase of seismic data have been used as seismic attributes along with the impedance logs to predict the impedance logs at the well locations. Figure 3 shows the actual and predicted impedance logs of the wells. A total of 25 sigmas have been used for training with the value of sigmas ranging from 0.1 to 3, with the global sigma of 0.825 is used.

A crossplot of actual and predicted impedance values using points from the analysis windows of all five wells is shown in Figure 4. The correlation coefficient for the linear regression using 3 attributes is 0.8287 with an average error of 3440.42 [(ft/s)*(g/cc)]. However, the validation results of PNN show a cross correlation coefficient of 0.7012 with an average error of 4152.23 [(ft/s)*(g/cc)] (Figure 5). PNN based prediction of impedance logs retains more of the dynamic range and high-frequency content as can be seen at the well locations, because the PNN result is a nonlinear function and closely follows the training or control data.

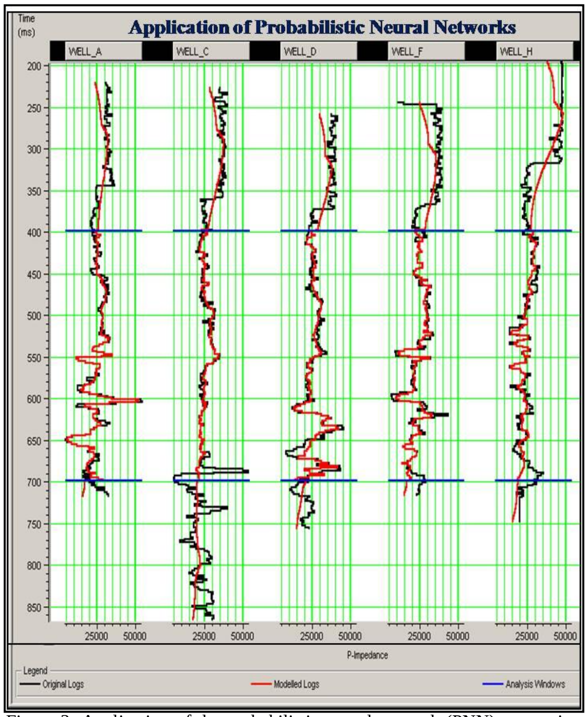

Figure-3: Application of the probabilistic neural network (PNN) comparing the predicted impedance logs and the impedance logs that were used in the training

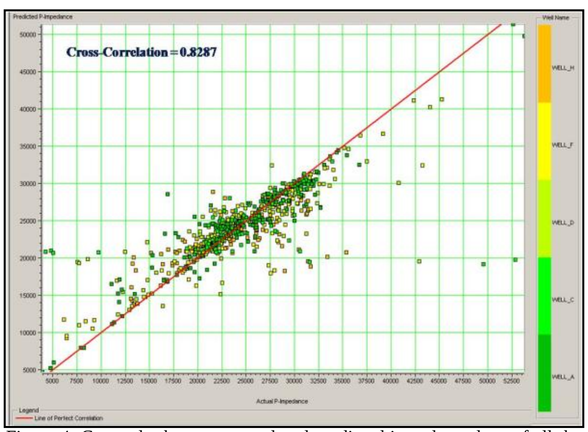

Figure-4: Cross-plot between actual and predicted impedance logs of all the wells.

The training values that we computed are applied to the whole seismic data volume to invert it into impedance volume. Figure 6 shows line that intersects the well-A extracted from the impedance volume. The vertical as well as the lateral resolution of the volume has been increased. This figure clearly shows the distribution of high impedance shales with moderate to low impedance coals.

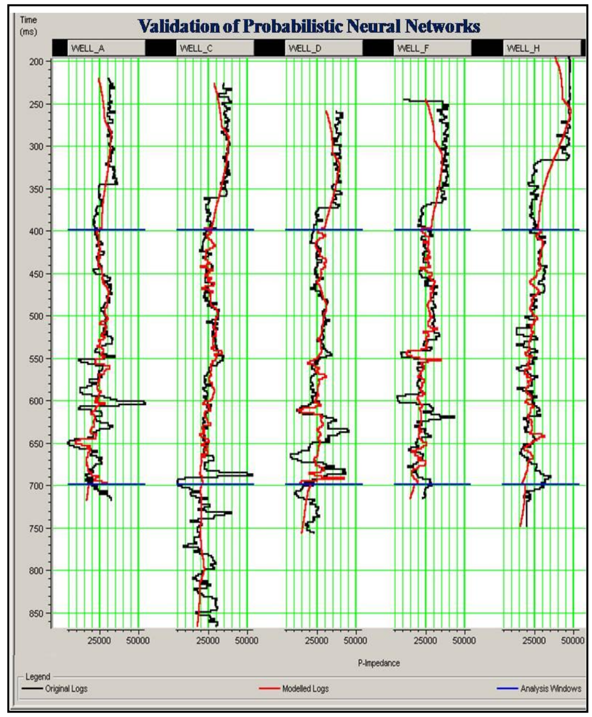

Figure-5: Validation of the PNN using the predicted and actual impedance logs

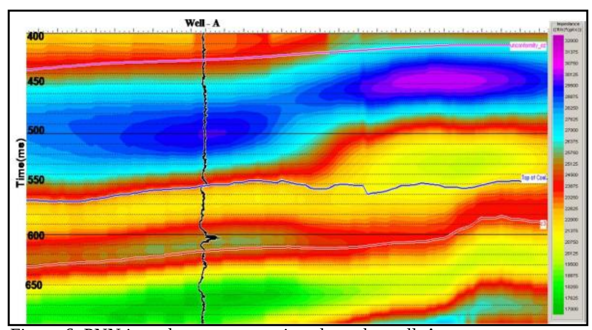

Figure-6: PNN impedance cross section along the well-A

The impedance volume has been viewed by extracting impedance values along the horizons, between the horizons and horizontal time slices to understand the deposition of coalbed methane reservoirs. Figure 7 shows a data horizontal slice extracted from the impedance volume. It clearly brought out the distribution of different lithofacies with lateral variation of impedance values.

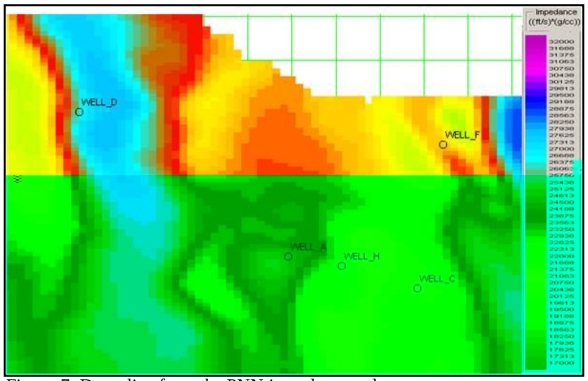

Figure-7: Data slice from the PNN impedance volume

Conclusions

The main advantages of the probabilistic neural network inversion of seismic data are not only improved the vertical and lateral resolution but it also uses cross-validation as a quality assurance tool. The tie between seismic and well logs is very important especially in case of thin bed reservoirs. We used PNN to invert the seismic data to exploit the thin bedded coalbed methane reservoir. PNN also gave better results when compared to other methods like band-limited, colored, sparse-spike inversion techniques.

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EDITED REFERENCES

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