

Porosity from Artificial Neural Network Inversion for Bermejo Field, Ecuador

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Summary

A porosity cube was generated using artificial neural network (ANN) inversion to populate a reservoir model for a producing zone in Bermejo Field, Ecuador. The stratigraphy and structure for the producing sand was extremely complex, and interpolation and conventional inversion techniques did not satisfactorily predict lateral and vertical variability within the volume. Porosity predicted by ANN correlated favorably with observed porosity at wells, and highlighted gas-bearing sands and lateral transitions between high- and low-porosity sands.

Introduction

As part of a cooperative reservoir characterization project between Tecpetrol and the University of Oklahoma, a reservoir model of the Hollin sand in Bermejo Field, Ecuador, was generated. The reservoir model required quantification of porosity throughout the volume, covering an area of approximately 9 x 13 km. Available data covering the area of interest included logs from 45 wells, and AGC migrated, NMO corrected 3D seismic shot in 2000 and interpreted as part of the reservoir characterization project. The Hollin formation is of fluvial to estuarine origin, and consists of interbedded sands and shales that are laterally discontinuous. The stratigraphy is further complicated by large- and small-offset faults, some of which were reactivated during basin inversion. Because of the complex stratigraphy and structure, simple interpolation of porosity among wells could not yield satisfactory results. Instead, it was necessary to rely upon seismic data to create a clear picture of and quantify lateral and to some extent vertical variability throughout the volume of interest.

Method

An impedance cube was generated for the volume of interest by seismic inversion, using commercially available software. The results were correlated with well logs for wells not used to generate the initial model. In general, the results were good: high acoustic impedance intervals correlated with producing sands, and low acoustic impedance intervals with shales. However, as to be expected, high acoustic impedance sands also locally corresponded with tight sands, and low acoustic impedances were observed in gas-bearing sands. Geostatistical correlation of porosity at the wells with impedance across the volume was not definitive.

To correct for these ambiguities, a porosity cube was generated using artificial neural network (ANN) inversion. ANN's are an attractive alternative to conventional inversion methods due to their ability to "learn" and "estimate" (Liu et al., 1998). Since ANN can learn the relationship between well data and seismic records, a correct forward modeling algorithm is not required. Also, as long as there is some kind of relationship, and to find the relationship is the ANN's job, between the well data and seismic records, the inversion can be successfully performed.

Among the ANN models, the backward propagation (BP) model is one of most effective. It is a feedforward network trained by error back-propagation. When it has one hidden layer, its approximated function is universal (Hornik, 1989). In the learning stage of a BP neural network, the output error is propagated backward, and the link weights of the network are modified with the propagation of error. When the total error is decreased to a given level, the network arrives at the relationship between the input and the desired output. This relationship is saved in weights which are encoded in the network.

Figure 1 shows the structure of BP neural network and the input data we used. Seismic data and the low frequency component of the well logs are used as input and the well log as desired output to train the neural network.

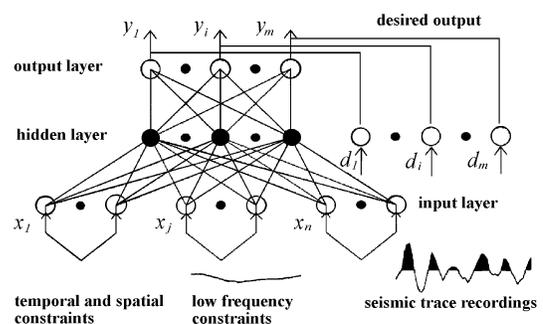


Fig. 1. Structure of backward propagation neural network and data used to generate porosity cube.

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The weights between layers of the network are modified iteratively until the differences between the output and desired output are less than a given level. After training, the seismic traces are input into the ANN algorithm and ANN predicts the well log response from the seismic data.

In the training of ANN, five seismic traces near each well were used. Thirty-one wells were used to train initially, and the remaining wells were used to test the results. When the desired results were achieved, all wells were used to train so that porosity at the wells in the porosity cube would match porosity data at the wells in the reservoir model. Porosity logs were calculated from neutron and density logs, and corrected for shale content or gas effect.

The result for training and testing is shown in Figures 2 and 3.

Conclusions

Observed porosity from the ANN inversion compared favorably with predicted porosity at most testing wells.

Isolated exceptions occurred when the testing well was separated from all training wells by faults with significant offset. In addition, the porosity cube compared favorably with the impedance cube, with the added benefit of being able to distinguish between high porosity sands and tight sands, and between gas-bearing sands, and other low impedance intervals (Figure 4). The porosity cube also shows improved vertical and lateral resolution over the impedance cube.

References

Hornik, K., Multilayer feedforward networks are universal approximators, *Neural Networks*, 1989, Vol. 2, No. 5, pp. 359-366.

Liu, Z., Liu, J., Castagna, J., and Pan, C., An iterative inversion of seismic data constrained by wells using artificial neural networks, *Offshore Technology Conference* 8726, 1998.

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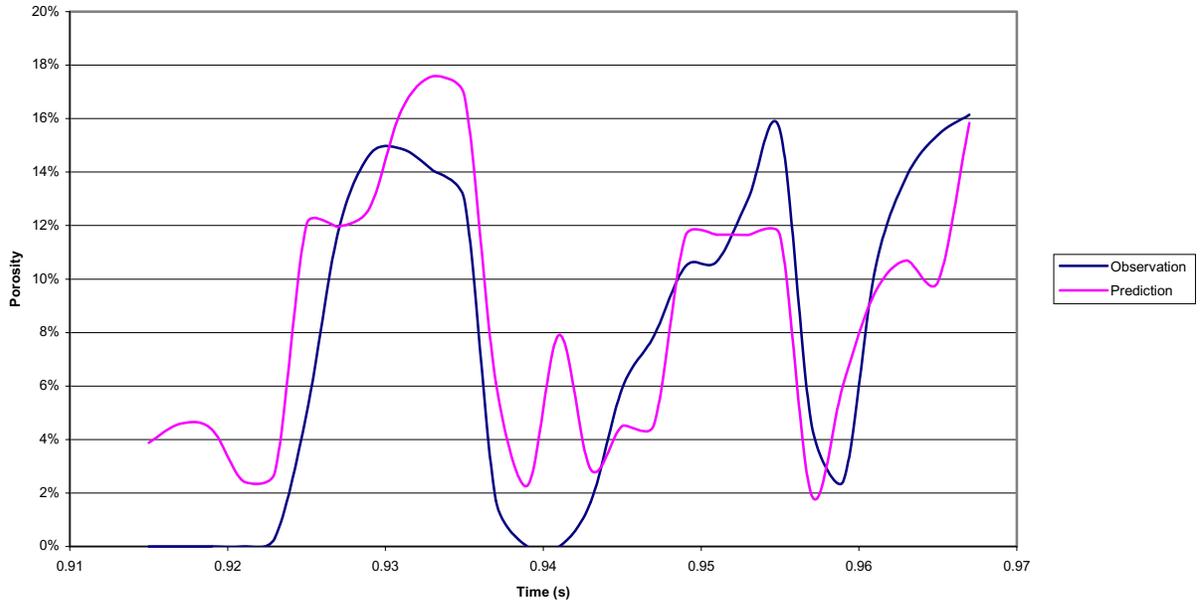


Fig. 2. BS-04 (training well), observed porosity vs predicted porosity

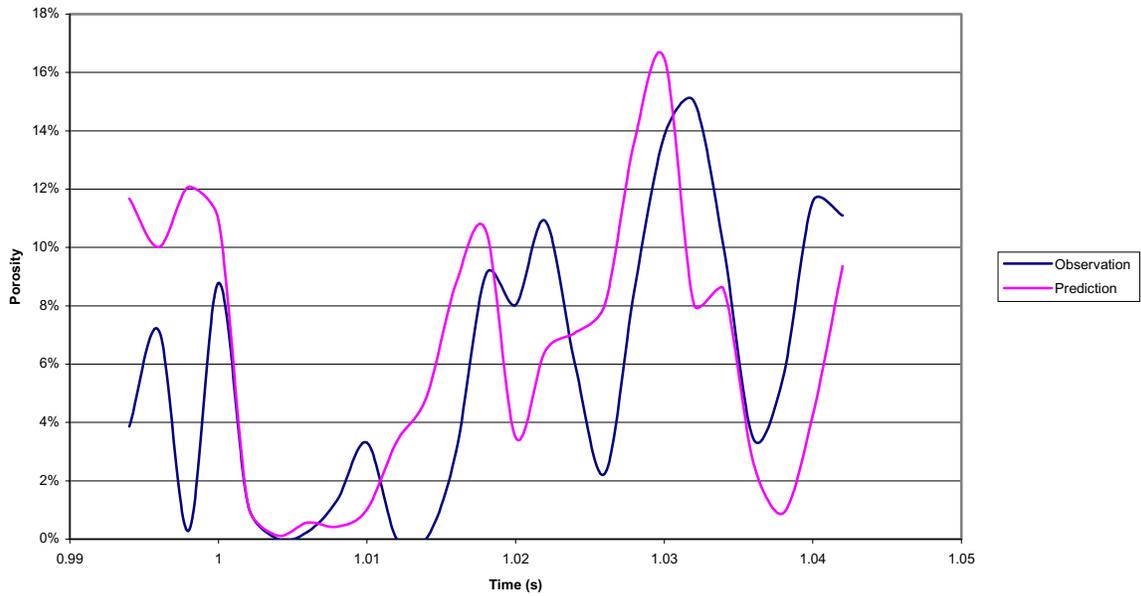


Fig. 3 BN-17 (Predicting well), observed porosity vs predicted porosity

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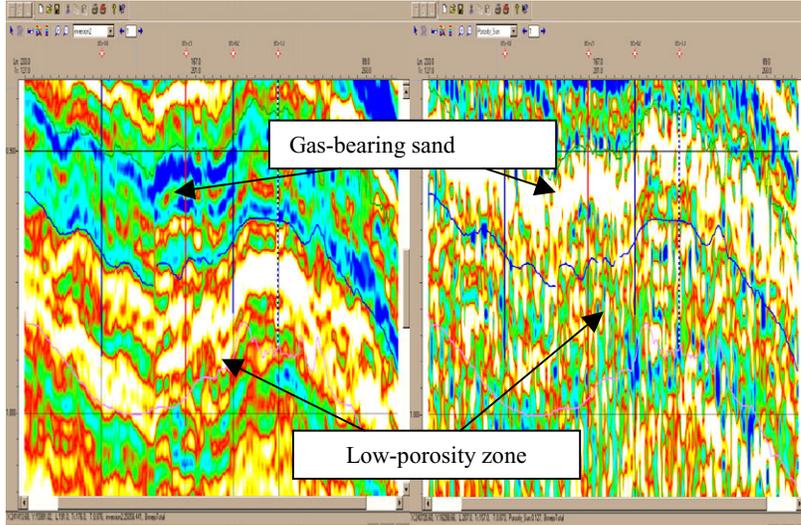


Figure 4. Left shows results of inversion for impedance. High acoustic impedance is shown in white, yellow and red, low acoustic impedance in blue and green. Right shows porosity cube for same interval. High acoustic impedance tracks high porosity except where shown.