Evaluation of Radial Basis Function Neural Networks in Reservoir Characterization of Caddo Member in Boonsville Field, Texas*

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Abstract

Geophysical reservoir characterization requires building a nonlinear relation between seismic attributes and rock/fluid properties computed from well logs. With such a relation, the rock/fluid properties computed from well logs can be extended to inter-well points. Neural networks can be employed to obtain this nonlinear relation. In this study, radial basis function (RBF) neural networks are evaluated in the application of porosity prediction. The structure of a typical RBF network is composed of an input layer, an output layer and a hidden layer. Currently, RBF network is only used as single hidden layer network in geophysics applications; however, multilayer RBF networks have already been dealt with by some researchers (Chao et al., 2001) and according to their study, there exists a performance improvement when multiple hidden layers are used. This study explores the possibility of applying multilayer RBF networks in reservoir characterization, dealing with well logs and seismic data and to design an optimal structure for a RBF network with fixed number of nodes. The seismic and well log data used in this study are the public part of the Boonsville 3-D seismic dataset, which is from the Boonsville field in north central Texas. A series of tests are carried out to examine performance and inspired by the comparative results of RBF and multilayer perceptron (MLP) networks, a hybrid of RBF and MLP called centroid based multilayer perception (CMLP) network is employed for porosity prediction. Finally, the best CMLP network is used for porosity prediction. Porosity distribution map constructed from seven seismic attributes using a triple layer CMLP neural network shows good correlation with well data. Because of the assumptions and approximations during the processes of porosity log prediction, porosity downscaling and neural network prediction, the average porosity prediction error is around 20%.

Reference Cited

Introduction
Subsurface seismic characterization requires building a relationship (commonly non-linear) between seismic attributes and rock/fluid properties. With such a relationship, the rock/fluid properties computed from well logs can be extended to interwell points (Figure 1). Neural networks are powerful tools to obtain this non-linear relation. In this study, radial basis function (RBF) neural networks with different structures are evaluated and applied to porosity prediction. A hybrid of RBF and multilayer perceptron neural networks (MLP) shows the best performance in this study.

Structure of Neural Networks
Figure 4: The traditional pattern of a single layer RBF neural network.
Figure 5: A typical multilayer RBF neural network with 2 hidden layers.

Testing of Neural Networks and Porosity Mapping
Tests are propelled with a group of inputs (7 seismic attributes including acoustic impedance) and an output (porosity). A total number of 14 wells are used in this study, among which 10 are in the training group and the other 4 act as testing group. Data in training group are randomized and 20 percent of which are used for cross-validation. Mean square error (MSE) is used to evaluate the networks’ performance. MLP networks are used for comparison. An evolution of RBF—centroid-based multilayer perceptron (CMLP, which means a MLP network with radial basis functions in the first hidden layer, just like a hybrid of RBF and MLP) network gives the overall best performance among all tested neural networks.

Table 1: Training error (T MSE) and cross-validation error (CV MSE) for RBF, MLP and CMLP networks. In the “structure” column, “20” means one hidden layer and 20 nodes in this layer, and “100 100” means two hidden layers with 100 nodes in each layer. ‘G’ refers to Gaussian, and ‘T’ refers to hyperbolic tangent. The overall best performance (shown as yellow cells) appears at CMLP with “G40 T24 T4” or RBF “100 100” (if excluding CMLP types).

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<thead>
<tr>
<th>Structure</th>
<th>RBF</th>
<th>MLP</th>
<th>CMLP</th>
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<td>20 MSE</td>
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Conclusions
Multilayer RBF neural network outperforms traditional single layer RBF networks, but an increase of the number of hidden layers will not guarantee an increase of performance. In this study, 2 hidden layers is the most suitable case. CMLP, the hybrid of RBF and MLP powered by genetic algorithm can give an overall best performance for this study.

Data
A time-migrated seismic volume and 14 wells which are from the public part of the Boonville 3-D seismic data set are used for this study. Log prediction for sonic curves is deployed to overcome the log deficiency. Interval between MFS90 and MFS20 is used to train and test the neural networks. Final porosity prediction is done along Caddo (Figure 3).

Research Procedure
Figure 7: Flowchart for training a neural network and applying it for prediction.

Figure 1: A model showing expanding the rock/fluid property at well locations to interwell space using the relation between seismic data and well log data.

Figure 2: The study area is located in Boonville Field in the Fort Worth Basin, north central Texas.

Figure 3: Stratigraphic nomenclature in Bend Conglomerate. Red lines indicate the interval used for training and testing neural networks. Black box indicates the Caddo.

Figure 4: A typical multilayer RBF neural network with 2 hidden layers.

Figure 5: A model showing expanding the rock/fluid property at well locations to interwell space using the relation between seismic data and well log data.

Figure 6: Typical structure of a centroid-based multilayer perceptron (CMLP) neural network.

Figure 7: Flowchart for training a neural network and applying it for prediction.