PS 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

Chao, J., M. Hoshino, T. Kitamura, and T. Masuda, 2001, A multilayer RBF network and its supervised learning: International Joint Conference on Neural Networks, 2001 Proceedings, July 15-19, 2001, Washington, DC, v. 3, 1995-2000.

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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.

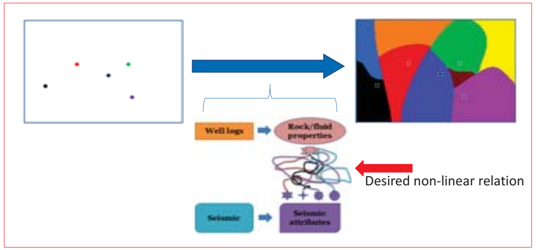

Figure 1: A model showing expanding the rock/fluid property at well locations to interwell space using the relation between seismic data and well log data.

Data

A time-migrated seismic volume and 14 wells which are from the public part of the Boonsville 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).

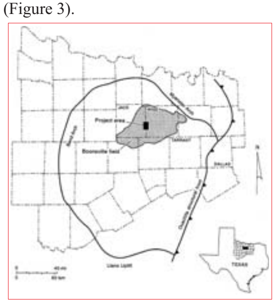

Figure 2: The study area is located in Boonsville Field in the Fort Worth Basin, north central Texas.

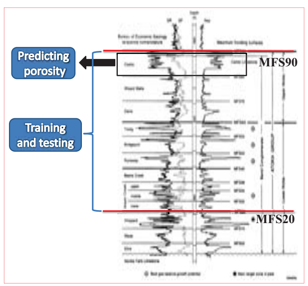

Figure 3: Stratigraphic nomenclature in Bend Conglomerate. Red lines indicate the interval used for training and testing neural networks. Black box indicates the Caddo.

Structure of Neural Networks

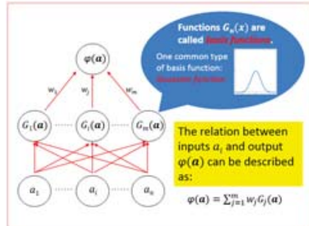

Figure 4: The traditional pattern of a single layer RBF neural network.

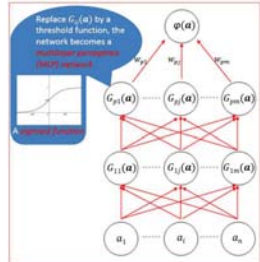

Figure 5: A typical multilayer RBF neural network with 2 hidden layers.

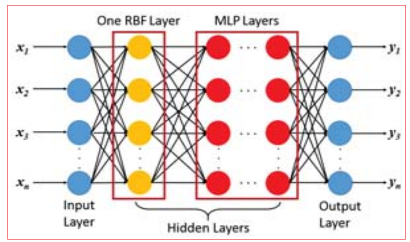

Figure 6: Typical structure of a centroid-based multilayer perceptron (CMLP) neural network.

Research Procedure

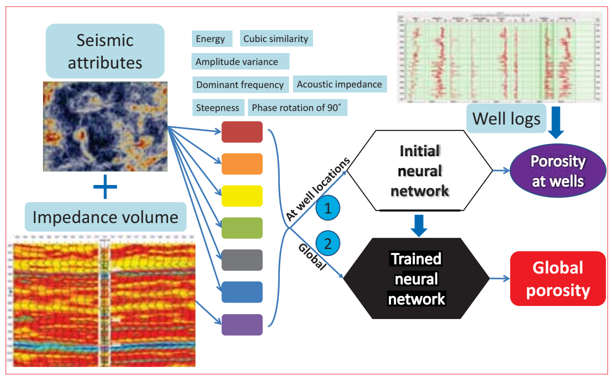

Figure 7: Flowchart for training a neural network and applying it for prediction.

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 a overall best performance among all tested neural networks.

Testing results for neural networks with different structures

By Training MSE

Type	Structure				T MSE	CV MSE
MLP	20				0.009665	0.027259
MLP	10				0.015336	0.02849
RBF	100	100			0.019249	0.0206
MLP	200	200			0.020053	0.022095
RBF	100	50			0.0202	0.024914
RBF	80				0.020375	0.020902
MLP	50	50	50		0.02042	0.020888
MLP	50				0.020461	0.022514
MLP	100	100	100	100	0.020861	0.023116
MLP	100	100			0.020924	0.021635

By Cross-validation MSE

Type	Structure				T MSE	CV MSE
RBF	100	100			0.019249	0.0206
MLP	50	50	50		0.02042	0.020888
RBF	80				0.020375	0.020902
RBF	10	5			0.023315	0.021081
MLP	50	50	50	50	0.021293	0.021257
RBF	25				0.022668	0.021306
RBF	150				0.022012	0.021494
RBF	5	20			0.022757	0.021495
RBF	50	50			0.022334	0.021519
RBF	5	100			0.023327	0.021524

CMLP Neural Networks

Structure					T MSE	CV MSE
T22	G50				0.020618	0.023727
G44	T14				0.019483	0.021734
G40	T24	T8			0.018875	0.020508
G44	T20	T19	T9		0.02136	0.02153
G39	T20	T20	T13	T9	0.02141	0.022151

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 T8" or RBF "100 100" (if excluding CMLP types).

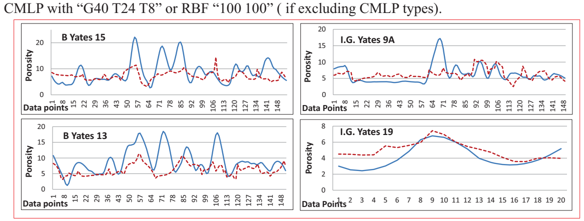

Figure 8 (up): Testing results for four wells using CMLP "G40 T24 T8". Blue solid curves are desired outputs and maroon dashed curves are predicted outputs.

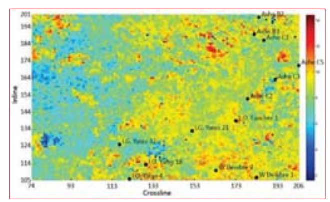

Figure 9 (left): Average porosity below horizon MFS90 with a window 30 ms obtained by CMLP "G40 T24 T8".

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 mapping for this study.