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Application of Multilayer Feed Forward Neural Network - Porosity Mapping in Gas Hydrate Sediment of K-G Basin, India

D.K. Singha* (Indian School of Mines, Dhanbad), R. Chatterjee (Indian School of Mines) & K. Sain (CSIR/National Geophysical Research Institute)

SUMMARY

Porosity has been estimated in the gas hydrate bearing sediments in Krishna-Godavari (K-G) basin at site National Gas Hydrate Programme (NGHP) 01-10 using multilayer feed forward neural network (MLFN). A series of elastic parameters namely P-wave velocity (V_p), S-wave velocity (V_s), density (D_n), V_p/V_s , P impedance (Z_p) and S impedance (Z_s) have been derived from seismic data using pre-stack inversion. The porosity (ϕ_D) estimated from the density log for the depth interval 1024-1224m is ranging from 51.6 to 82.6 %. The estimated porosity has been treated as target log and Z_p , Z_s , V_p/V_s and D_n have been used as input parameters during the training of MLFN. The trained network is then used to train the network to generate subsurface porosity along a 2D multi channel seismic section (line-16) at site NGHP01-10 within the time interval of 1.433 – 1.631s corresponding to the depth interval of 1024-1224m. The predicted porosity is decreasing in gas hydrate stability zone (GHSZ) and is varying laterally. Porosity is increased in the free gas bearing zone below the base of GHSZ

Introduction

Krishna-Godavari (K-G) basin is a petroliferous basin, producing oil and gas, located near the mid portion of eastern continental margin of India (ECMI). It holds a large number of structures and traps which have been identified for drilling in the onland and offshore parts of the basin (Rao, 2001). Gas hydrate distributions in the sediments of K-G offshore are commonly inferred from the occurrence of bottom simulating reflector (BSR) lying at the base of the gas hydrate stability zone (GHSZ) (Shankar et al., 2011). The presence of gas hydrate within the sediments increases the velocity while free gas decreases the velocity thus creating a strong impedance contrast across the base of GHSZ. A series of elastic parameters namely P-wave velocity (V_p), S-wave velocity (V_s), density (D_n), V_p/V_s , P impedance (Z_p) and S impedance (Z_s) have been derived from multi channel seismic data using pre-stack inversion. The porosity (ϕ_D) has been estimated from the density log of well-10A for the depth interval 1024-1224 m and is ranging from 51.6 to 82.2 %. The estimated ϕ_D has been treated as target log and Z_p , Z_s , V_p/V_s and D_n have been used as input parameters during the training of multilayer feed forward network (MLFN). The trained network is then used to train the network to generate subsurface porosity along 2D seismic section (line-16) at site NGHP01-10 within the time interval of 1.433 – 1.631s corresponding to the depth interval of 1024-1224m.

Method and theory

The total porosity has been calculated from density log using following equation

$$\phi_D = \frac{(\rho_m - \rho_b)}{(\rho_m - \rho_f)}$$

ρ_m , matrix density = 2.65 g/cc; ρ_f , fluid density=1.08 g/cc and ρ_b ., bulk density of the formation (from density log)

Figure 1 Density, porosity and resistivity log are displayed. BSR is clearly identified from resistivity log at 1.203s and at depth 1203m.

Neural networks have been used frequently since several years in geosciences for computation of different rock properties from geophysical data. MLFN networks, trained with a back-propagation learning algorithm, are the most popular neural networks. MLFN uses to predict log properties directly from seismic data (Liu and Liu, 1998, Hampson et al, 2001). The objective of training the neural network is to find a weight vector which minimizes the difference between the actual output and the desired output. The problem of estimating the weights can be considered as a nonlinear optimization problem, where the objective is to minimize the mean-squared error between the actual target log values and the predicted target log values (Hampson et al, 2001). A MLFN network has been constructed in which porosity log of well-10A acts as an input log and four seismic attributes namely; Z_p , Z_s , V_p/V_s and D_n have been considered as input parameters. The operator length of network is 3; pre-whitening used during training is 0.1%. The neural network parameters:

number of nodes in hidden layer is 5, number of iterations is 10 and number of conjugate iteration is 100. The training error is 4.6% where validation error is 8.2%.

Result

Figure 2 the porosity section after applying the trained network on the line-16 showing the porosity values laterally and vertically varying with depth.

The predicted porosity is observed to decrease in the gas hydrate stability zone and varies laterally. The porosity trend follows the geologic structure of the basin. Porosity is increased in the free gas bearing zone below the base of GHSZ.

Conclusions

A pre-drill estimate of porosity has been obtained from seismic data using seismic attributes transform through MLFN analysis. The seismic attributes have been calculated using pre-stack inversion. The training and validation error are low, suggesting reliable porosity determination using network application. The estimated porosity values may be erroneous beyond the drilled depth because of non availability of well log data.

Acknowledgements

Authors are very much thankful to Director, NGRI, Hyderabad for providing the required data to prepare this work. MoES has been acknowledged for giving us financial support.

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