B047 RESERVOIR CHARACTERIZATION FROM 3D SEISMIC DATA USING ARTIFICIAL NEURAL NETWORKS AND STOCHASTIC MODELLING TECHNIQUES

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For an accurate prediction of the production profile of a hydrocarbon reservoir an optimum assessment of the geological reservoir model is required. The reservoir architecture and litho-stratigraphic properties of the model are most important boundary conditions in the economic evaluation of the reservoir. Integration of data from different sources, with widely varying resolutions and accuracies is a pré-requisite to achieve this goal.

In this paper a method is described in which seismic data is inverted by feed-forward layered neural networks. The networks are trained to recognize seismic responses in terms of meaningful reservoir parameters, such as reservoir porosity or net-to-gross pay zone ratio. The trainingset is compiled by integrating information from various types of data.

The proposed methodology starts with the extraction of a horizon slice from a migrated and interpreted 3D seismic data set. This stratigraphically constrained slice is then conditioned, i.e. converted to zero-phase reflectivity with the use of available well log synthetic seismograms. The next step is to establish whether a relationship exists between the seismic response and a meaningful reservoir parameter. Because of the limited bandwidth of the seismic response any such relationship will be non-unique in nature. In order to arrive at the optimum relationship, constraints have to be built in which take into account all available geological information. In this method, these constraints are set as à-priori information in the dataset that is used to train the neural networks. Two approaches are used: a deterministic approach and a stochastic (or Monte Carlo) approach.

In the deterministic approach the networks are trained on a dataset that is compiled from data at well locations. The seismic response at the well location is fed to the input nodes of the network while the corresponding well results are fed to the output nodes. This method can be applied on existing fields with sufficient well control only.

The stochastic approach can be employed in area's with limited well control. Here synthetic seismograms, in one- two or three dimensions, are created by stochastically varying the model input parameters, such as layer thicknesses, sonic and density values, hydrocarbon contents etc.. These parameters and their distributions are based on the available geological data and knowledge which ensures that any relationship to be established by the neural networks will be properly constrained. The generated synthetic models are subsequently conditioned to resemble the real data (i.e. the same wavelet and scaling must be applied). The networks are trained by feeding the conditioned synthetic seismograms to the input nodes and one (or more) of the underlying model parameters to the output nodes.

In both methods the trained networks are tested on independent data sets. In the deterministic approach the independent dataset consists of data at well locations not used for training the networks. In the stochastic approach, independent synthetic seismograms, are used to test the network's performance. The trained and tested networks are subsequently applied to the real seismic data yielding a number of XYZ-grids for the requested reservoir parameters.

The techniques discussed in this paper are presently being implemented in an industrial quality software package by the "Probe" consortium.