Technical Note #14

TEEC

Seismic Facies Classification of Deep Rotliegend Sandstones by Neural Network Techniques

Application of TEEC´s *neuro*TEEC Software

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In order to predict the reservoir quality of deep (4500-5000 m) Rotliegend sandstones in the North German Basin a Neural Network approach has been applied and compared to conventional amplitude investigations. As the result of this study the Neural Network is able to detect trends of varying reservoir quality throughout the survey, whereas no reliable information could be obtained from simple amplitude investigations.

1. Introduction

This paper describes the use of an artificial Neural Network to predict area-wide reservoir parameters by classifying 3D seismic subpattern from 3D seismic data. Special emphasis is placed on the comparison between the artificial Neural Network and conventional amplitude investigations. The target of this study are Rotliegend sandstones within the North German Basin. The reservoirs are found at a depth of 4500 – 5000 m. For this investigation, an area of 220 km^2 was selected, covered by 9 wells which have tested the reservoirs.
A number of studies (Budny 1991; Hartung et al. 1993; Trappe et al. 1998), among others, have dealt with the 3D seismic reservoir characterisation of the North German Basin. All studies have shown the impact of seismic data on reservoir quality prediction. The specific problem of this study area is that traditional amplitude investigations do not result in a reliable forecast, and more advanced techniques are required. A Neural Network could be a solution for mapping reservoir quality from seismic data. In general, a Neural Network is able to handle multivariate, redundant data in a nonlinear fashion. Schulz et al. (1994), de Groot et al. (1998) and Trappe et al. (2000a and 2000b), among others, give examples of the successful application of artificial neural Networks in the field of reservoir characterisation.

2. Conventional Amplitude Approach

The seismic amplitude map of the investigated reservoir is presented in Fig. 1. On this map several amplitude anomalies are observed. In other parts of the basin these bright spots are often related to increased porosities, or increased reservoir quality in general. Numerous wells successfully confirmed this assumption. However, within the study area the interpretation of amplitudes only is rather questionable. In Fig. 2 amplitudes were extracted at location of key wells and plotted versus the known reservoir quality, which is parameterised as the product of porosity x thickness.

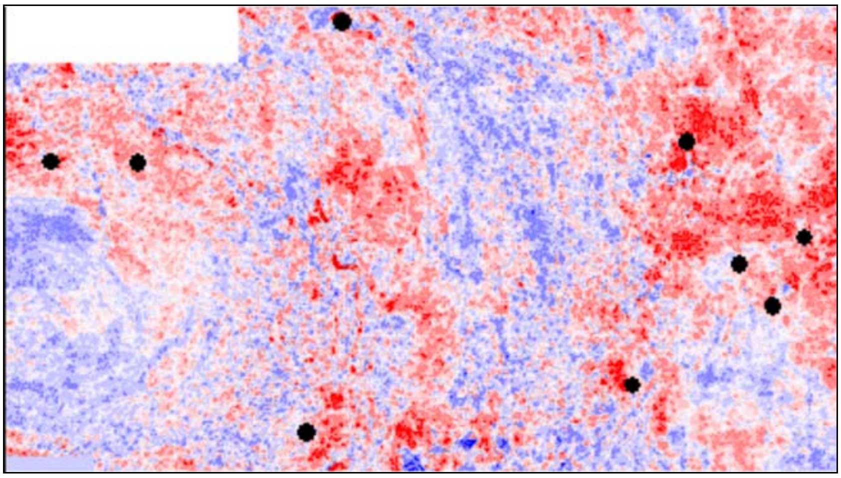

Fig. 1 Amplitude map at reservoir level

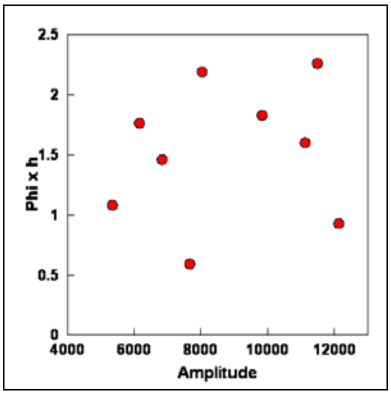

Fig. 2 Relationship between amplitude and porosity x thickness

From this result and other tested relationships the problem becomes obvious, no clear trend between amplitude and reservoir parameters exist. In Fig. 3 examples of seismic data quality are presented showing the complex seismic signal at reservoir depth. Aim of the study was to investigate whether a Neural Network approach could solve this problem.

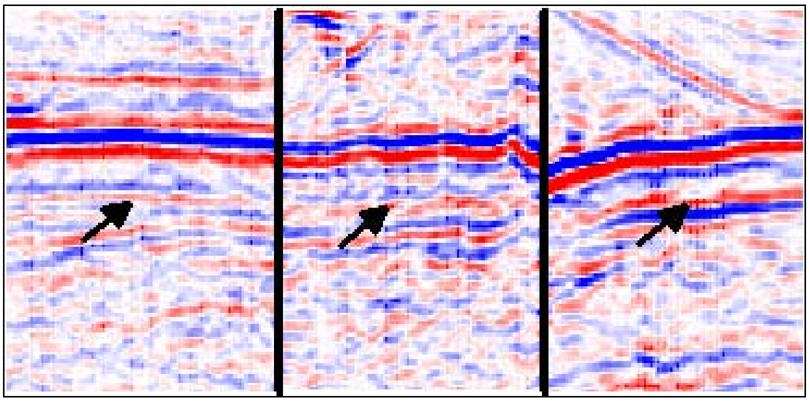

Fig. 3 Seismic examples showing lateral variation of seismic signal characteristics at reservoir depth

3. Neural Network Approach

In order to solve the problem a Neural Network (Self Organising Feature Map, SOFM) has been applied. The SOFM consists of a single layer of connected neurons (Kohonen 1988, Ritter et al. 1991). Different architectures can be used (Fig. 4). A self organising process adapts the neurons such that similar input pattern are mapped to neighbouring neurons on the SOFM. Our proposed workflow is based on the assumption that changes in lithology, rock properties and/or fluid content should affect the seismic traces with respect to amplitude, shape and lateral coherency. This leads to the approach to take advantage of three dimensional seismic patterns (subvolumes, Fig.5) where the individual characteristics of these pattern should be detected by the Neural Network.

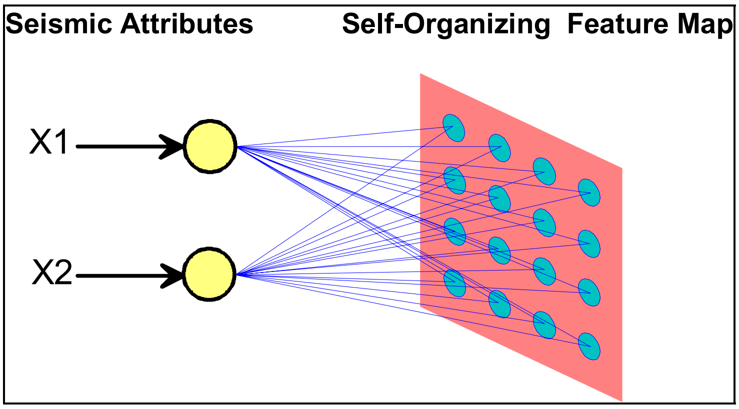

Fig. 4 Neural Network Architecture to Classify Seismic Data.

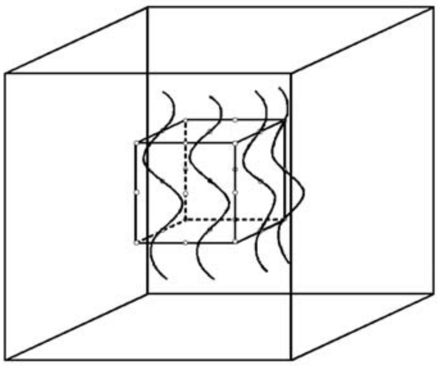

Fig. 5 Schematic illustration of the 3D seismic pattern to be classified by the Neural Net

Contrary to the generation of dozens of seismic attributes which may be related to the reservoir heterogeneity later on, the Neural Network comes with the spatial distribution of classes representing similar signal characteristics, or simply seismic facies classes. These seismic facies classes often represent features of the reservoir heterogeneity that are otherwise hard to detect or time consuming to interpret. A seismic facies map showing the laterally varying reservoir quality is presented in Fig. 6. This result was generated in a four step procedure:

- Extraction of 3D training patterns from the seismic data by a random process
- Setting up a network architecture, training and analysing of training results
- Classification of the whole seismic data and definition of seismic facies classes
- Calibration and verification of facies classes by means of key wells and geological information

A link between the Neural Network classification result and reservoir quality is represented by Fig. 7. As an example this diagram gives the relationship between seismic facies classes and the product of porosity x thickness at location of key wells.

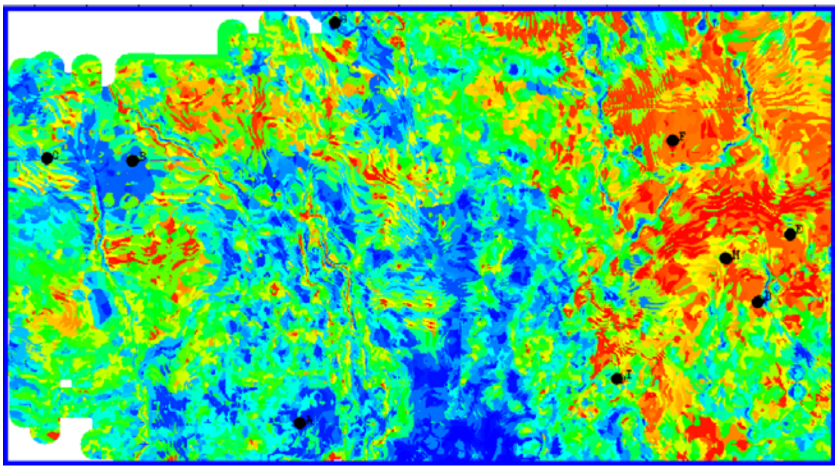

Fig. 6 Result of seismic facies classification by Neural Net

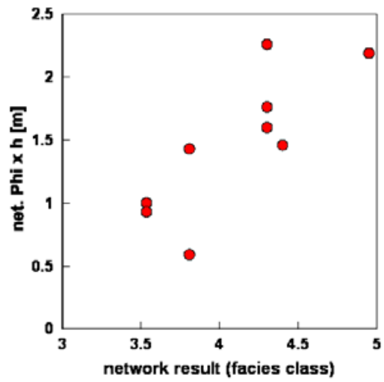

Fig. 7 Relationship between facies Class and porosity * thickness

Additionally other relationships were applied such as the dominant sedimentological environment, permeability and degree of cementation. This information can now be used to estimate the reservoir quality in undrilled areas.

As a second result during the course of the study several network architectures were tested, including variations of 1D and 2D Networks. Figure 8 illustrates the mapping of seismic facies to a 1D and a 2D network respectively. The 2D networks generally exhibits a superior classification and prediction capability.

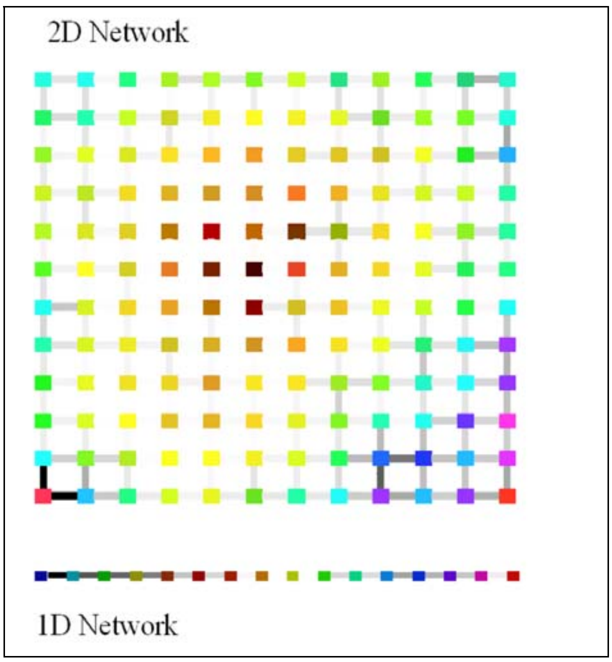

Fig. 8 Example for a 2D and 1D Neural Net architecture

4. Conclusions

A Neural Network approach was applied to map the lateral heterogeneity of the reservoir. The proposed approach results into seismic facies classes representing features of the reservoir properties. Well data is used to correlate between seismic facies classes and reservoir quality. This leads to an estimation of reservoir quality of adjacent areas where no well data is available.

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