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Seismic Reservoir Characterisation Using Artificial Neural Networks

1. Abstract

The aim of seismic reservoir characterisation is to relate seismic measurements to relevant geological and petrophysical reservoir properties. The process involves analysing complex relationships between huge amounts of data originating from different sources, acquired at different scale levels and accuracies. In the last decade artificial neural networks have been used successfully by many workers to aid in the process of finding these complex relationships. In this paper an overview is given of the current state-of-the-art and examples are shown of some popular neural network applications.

2. Introduction

Artificial neural networks or connectionist models as they are sometimes referred to, have been inspired by what is known as the 'brain metaphor'. These models try to mimic the capabilities of the human brain using computer hardware and software. The human brain has a number of properties that are desirable for artificial systems (e.g. Schmidt, 1994):

- It can deal with information that is inconsistent, or contaminated with noise.
- It can handle unforeseen situations by applying knowledge from other domains and extrapolating this to new circumstances.
- It can deal with large amounts of input data and quickly extract the relevant properties from that data.
- It is highly parallel, hence it has a high performance.
- It is robust and fault tolerant. Even if nerve cells in the brain die (which is known to happen every day), the performance of the brain does not deteriorate immediately.
- It is flexible. This means that the human brain can adjust itself to new situations and can learn by experience.

Neural networks have emerged in the last decade as a promising computing technique which enable computer systems to imitate some of the desirable brain properties. Various types of networks have been applied successfully in a variety of scientific and technological fields. Examples are applications in industrial process modelling and control, ecological and biological modelling, sociological and economical sciences, as well as medicine (Kavli, 1992). Within the exploration and production world, neural network technology is routinely applied to geologic log analysis (Doveton, 1994) and seismic attribute analysis (Schultz, 1994, de Groot, 1998).

Basically, two learning approaches can be recognised in neural network modelling:

1. supervised and
2. unsupervised.

The supervised approach requires the existence of a representative dataset. The network learns by feeding it examples from the representative dataset (the training set). The neural network then learns how the input data is related to the desired output. The supervised approach is a form of non-linear, multivariate regression that is used to quantify or classify data. Examples of quantification are networks that predict, from the seismic response, properties such as porosity or porevolume. Examples of classification are: classifying seismic waveforms into classes representing a specific fluid-fill, or a lithology. Popular supervised learning networks are: Multi-Layer Perceptrons and Radial Basis Functions networks (e.g. de Groot, 1995).

In the unsupervised approach the aim is to find structure in the data themselves, without imposing an a-priori conclusion. Unsupervised learning is used for data segmentation, i.e. data clustering. The resulting segments (e.g. clusters of similar seismic waveforms at the reservoir level) remain to be interpreted. Popular networks that use unsupervised learning are the Unsupervised Vector Quantiser (de Groot, 1995) and Kohonen Feature Maps (e.g. Lippmann, 1989).

3. Applications

Neural networks are simply a way of mapping a set of input variables to a set of output variables. In seismic reservoir characterisation the input obviously comes from seismic data. This can be in the form of amplitudes, or single and/or multi-trace attributes derived from one or more seismic volumes (e.g. full stack, near stack, far stack, intercept, gradient, inverted acoustic impedance etc). Input may also come from other sources (e.g. co-ordinates, two-way time, geological features etc). Basically any variable that is available at each prediction position and which may be related to the desired output can be used.

The output depends on the type and design of the network and how the trained network is applied. The results are two-dimensional (grids) if the network is steered along an interpreted horizon. Three-dimensional results (volumes) are obtained if the network is applied on a trace-by-trace and sample-by-sample basis.

3.1 Supervised learning

In supervised experiments for seismic reservoir characterisation a training set is constructed from well data with associated seismic information. The process comprises two steps (Fig. 1). First the network learns how seismic data are related to well data. Secondly the trained network is applied to the entire volume yielding the requested prediction result. It is good practice to use a number of examples as blind test locations. These wells are not used in the training procedure but are used to validate the result and to avoid overfitting the training set. Overfitting is a process, which may occur with prolonged training. The network must learn the relationship that has optimal predictive power. This is the relationship belonging to the network that produces the smallest error on the blind test data. The error on the training set may decrease further when training is continued but the error on the test set will increase. The reason is that the network starts to recognise individual examples from the training set and deviates from the general trend. Overfitting is especially a problem when the training sets are small (few wells) and the networks are large (many nodes in the hidden layer means more degrees of freedom, hence more complicated functions can be modelled).

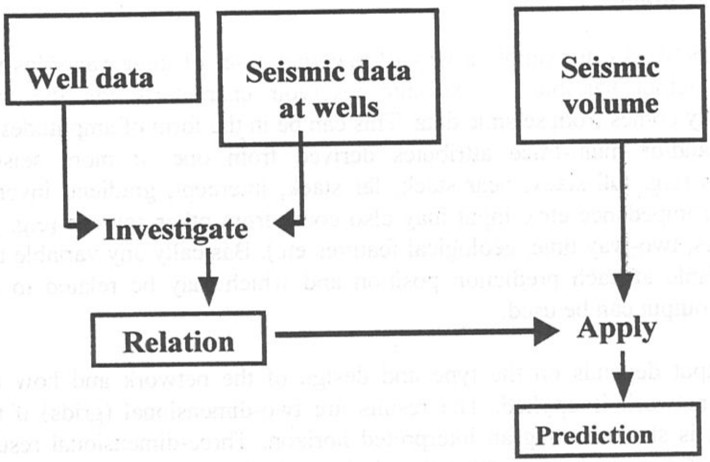


Fig. 1 *Generalised workflow for seismic reservoir characterisation. In supervised neural network applications* **'Investigate'** *corresponds to training the network, the* **'Relation'** *is captured in the trained network, which is subsequently applied to yield the* **'Prediction'** *result.*

In general there is only limited well control and thus there may be a problem that training and test datasets are not truly representative of the variations in the data. This problem can be bypassed by simulating additional pseudo-wells with associated synthetic seismograms (de Groot, 1996). The method assumes geologically and petrophysically correct simulations and good synthetic-to-seismic matches.

3.1.1 Quantification example

The example is from north-west Germany, where gas is present in the Rotliegend sandstones. Two 3D seismic volumes were available: zero-phase reflectivity and acoustic impedance. Six wells fall inside the study area. These were used to derive the statistical variations needed by the pseudo-well simulator and served as blind test locations to validate the predictions.

The objective was to transform the seismic information over the target interval into porosity. The principle of this technique is shown in Fig. 2.

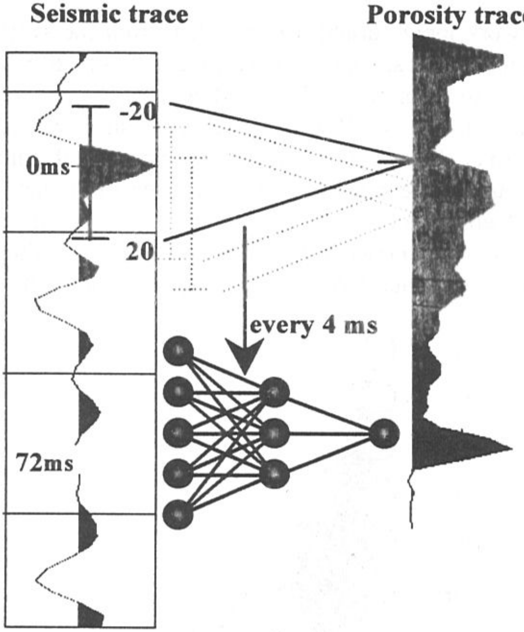


Fig. 2 *The principle of (supervised) volume transformation. Input and target variables for training and testing the network are extracted in a sliding window from seismic trace and target trace respectively. Application of the trained network on trace-by-trace and sample-by-sample basis yields a 3D prediction volume.*

Three hundred pseudo-wells with sonic, density (hence impedance) and porosity logs were simulated. The simulator is based on a constrained Monte Carlo procedure which is steered by geological knowledge (de Groot, 1995). Synthetic seismograms were made via the convolution model. Porosity traces were constructed from the simulated logs by converting the depth curve to two-way-time using the sonic log. The time curves were resampled with an anti-alias filter to 4ms. sampling. Porosity values were extracted as target quantities at every seismic sample position.

The neural network input variables were taken from the synthetics and the acoustic impedance traces. Seismic waveforms of [-20,20]ms. length were extracted relative to a reference time, sliding with 4 ms. steps between [-10,42] ms. relative to the Top Wustrow. Hence, seismic waveforms of 40ms. length were taken at -10, -6, -2 ms. etc. In the same way the amplitude of the synthetic impedance trace was extracted and given to the network. Also the reference time itself served as an additional input node to the neural network. Fig. 3 shows the neural network topology. To avoid overfitting 50 pseudo wells were used as test data during the training of the network.

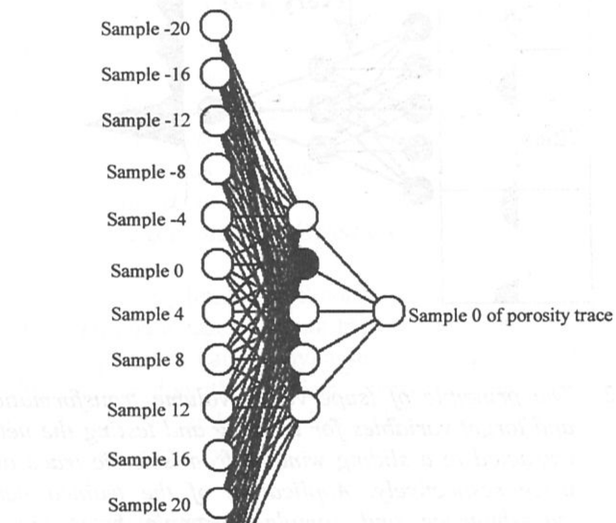


Fig. 3 *The fully connected Multi-Layer-Perceptron used to transform seismic waveforms + acoustic impedance + reference time into porosity.*

No synthetic-to-seismic matching is needed, as long as we train the neural network purely on the synthetic seismic data. The synthetic trace and the porosity trace are generated in the same way and thus have the same mispick and squeeze/stretch problems. A neural network trained in this way acts as a perfect transformation filter. Applying the neural network to the seismic cube yields a prediction cube with the stretch/squeeze and mispick problems as recorded by the seismic. Fig. 4 shows one inline through the porosity cube.

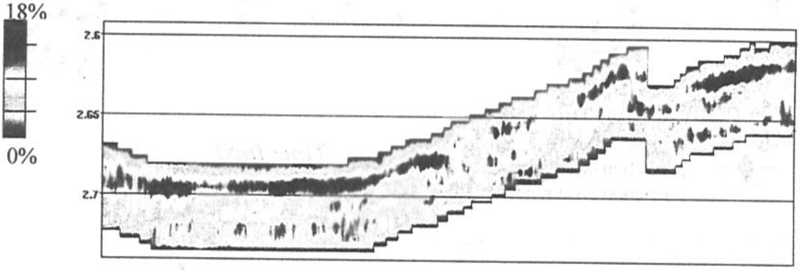


Fig. 4 *One inline through the predicted porosity cube.*

The result was validated at the real well locations. Fig. 5 shows the porosity predictions from real and synthetic data versus the original porosity trace at these blind test locations (one well in the vicinity of a salt dome was shifted to the optimal synthetic-to-seismic match position). All 6 blind test predictions are very good, hence increasing our confidence in the result.

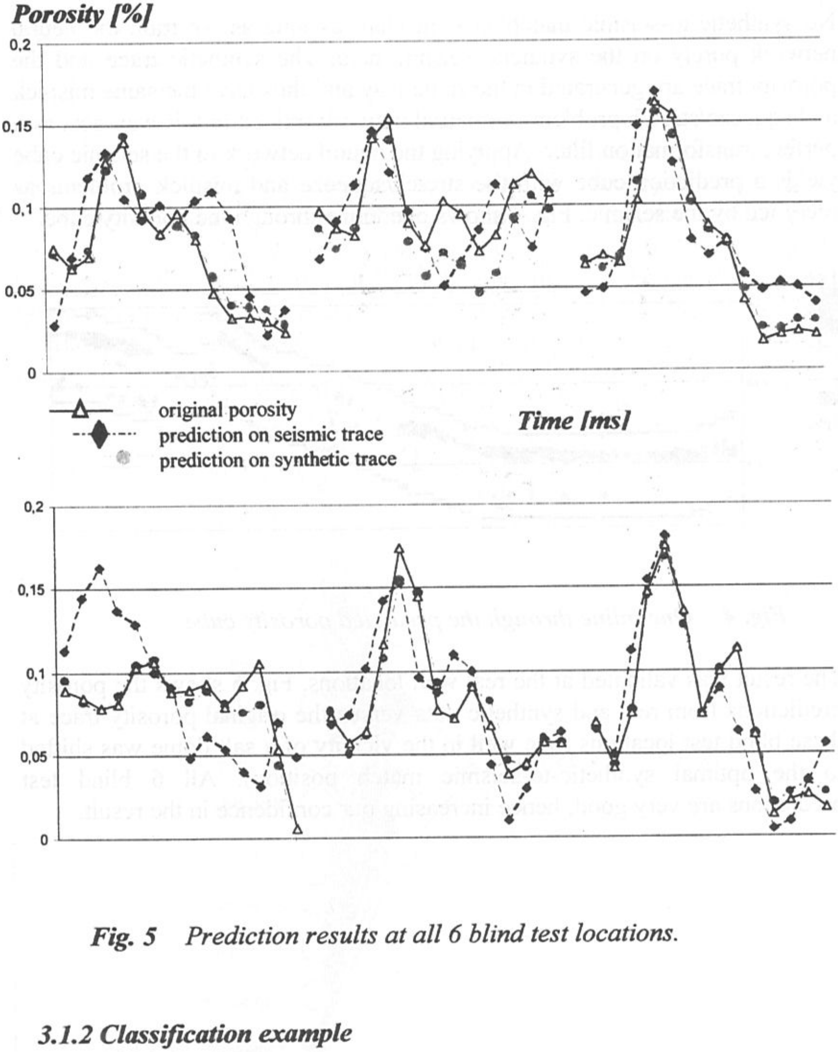


Fig. 5 Prediction results at all 6 blind test locations.

3.1.2 Classification example

The example is from the a mature oil field in Northern Germany. The Jurassic target interval comprises three sandstone units. Oil is produced from the middle unit: the Dogger Beta at a depth of around 1400m. The thickness of this unit varies between 10 and 30m. A revised fault interpretation based on recently acquired 3D seismic data revealed a heavily faulted structure with several undrilled blocks.

The objective of this experiment was to classify the Dogger beta seismic response into three classes representing oil-fill, mixed-fill and brine-fill. The training set was constructed from real seismic traces that were selected in drilled blocks only (Fig. 6). Locations near the top of the structure were considered oil-bearing. Traces near the interpreted oil-water-contact were assigned a mixed class and traces below the contact were representative for brine-filled. An 'oil-mix-brine' interpretation map provided by the client guided the selection.

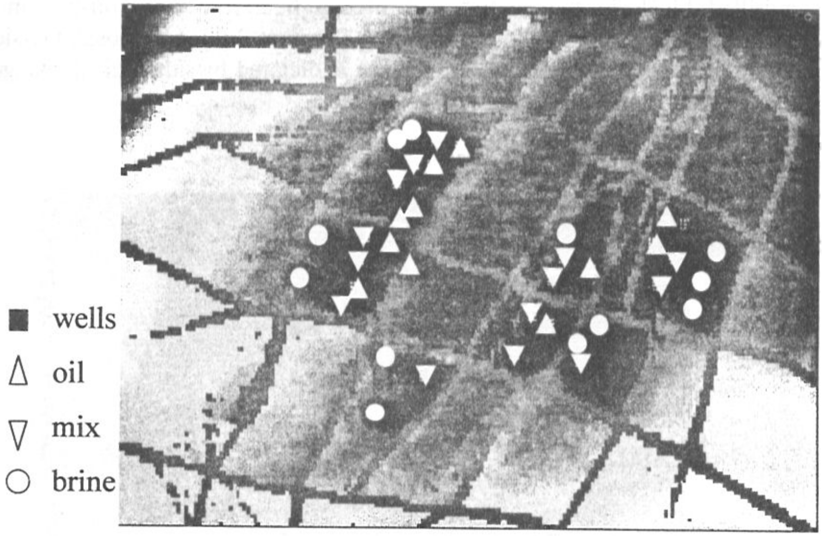


Fig. 6 *Time structure map with selected locations for training a Multi-Layer-Perceptron network to classify the seismic response into three classes representing oil-fill, mixed-fill and brine-fill.*

The training set constructed in this way comprised approx. 100 vectors per class. A fully connected Multi-Layer-Perceptron network was designed with

31 input nodes (amplitudes between -20 to +40 ms. at 2 ms. sampling), 9 hidden nodes and 3 output nodes corresponding to the classes. Given the biased nature of this experiment no independent test dataset was constructed. Training was stopped when the overall RMS. error on the training set reached a plateau. Application of the trained net to the entire seismic volume yielded two outputs per seismic location:

1. the index of the winning class (Fig. 7)
2. the match indicating the confidence in the classification (1=very confident, 0=no confidence)

The results are sensible in the immediate surroundings of the field. The undrilled block in the central part of the field indicates 'oil-fill' in a structurally high position, thus supporting a current drilling proposal. Outside the field boundaries the seismic response is dictated by lithological changes and the results are unreliable.

MLP predicted oil-mix-brine

***Fig.** 7 Neural network predicted fluid-fill.*

3.2 Unsupervised learning

Because of the volume of seismic data, unsupervised learning approaches for seismic reservoir characterisation generally involves two steps (Fig. 8, dashed squares). First a representative subset of seismic examples is extracted from the data. These are given to the network with the instruction to learn how to segment these examples into a (predefined) number of segments. The trained network is subsequently applied to the seismic volume to yield a segmentation result. This is a non-quantitative result showing only areas or objects with similar seismic characteristics. The meaning of these segments remains to be interpreted. On the right-hand side in Fig. 8 it is schematically depicted how the segmentation results can be quantified. A representative set of wells (real or simulated) is segmented by the network according to the corresponding (real or synthetic) seismic response. The segmentation result is used to analyse geological and petrophysical variations per segment.

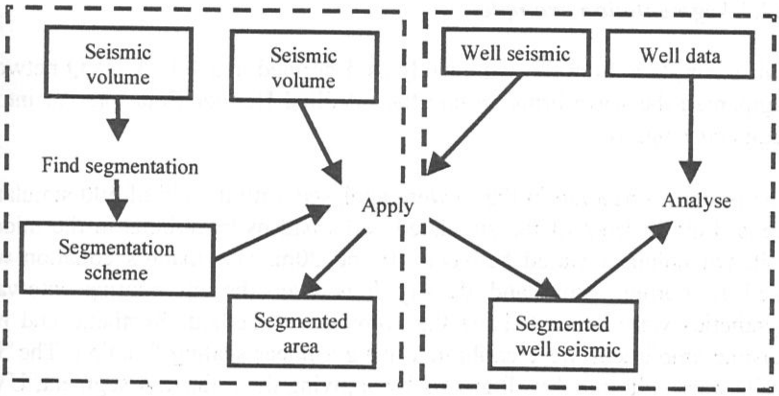


Fig. 8 *Generalised workflow for seismic reservoir characterisation using segmentation. The dashed square on the left shows the non-quantitative part of the process. 'Find segmentation' corresponds to training a neural network on a representative*

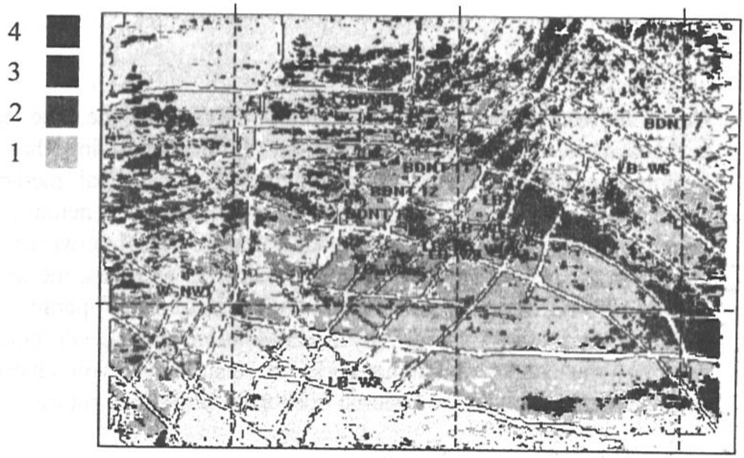
subset. 'Apply' *refers to application of the trained network yielding the segmentation result. The quantitative part is depicted in the right dashed square. This part requires the presence of a representative set of wells with corresponding seismic data. Application of the trained network yields a segmentation result that is used to analyse geological and petrophysical variations per seismic segment.*

For example, 1000 simulated wells with synthetic seismograms are used to explain the results of a 10 segment UVQ network. First the network is applied to the synthetics of each simulated well. The network thus decides to which of the 10 segments each well belongs. Subsequently, relevant well features (e.g. porosity, net-to-gross ratio, thickness, porevolume, fluid fill etc.) are extracted from the original well group (1000 simulated wells). Combining these features with the segment information reveals where the segments differ in terms of geological and petrophysical content.

3.2.1 Segmentation example

This example is from the same study as described in 3.1.1. A UVQ network segmented the waveforms around the oil-filled Dogger Beta interval into 4 segments (Fig. 9).

The patterns observed in Fig. 9 were analysed with the aid of 500 simulated wells. Fifty percent of the simulated wells had hydrocarbons in the middle unit. Oil columns varied between 10 and 20m. Gassmann's equation was used to correct sonic and density logs over the oil bearing intervals. Synthetics were generated via the convolution method. Synthetic and real seismic amplitudes were calibrated using a linear scaling function. The 500 wells were split into 4 well groups by applying the trained, 4 segment, UVQ network to the synthetic seismograms. The resulting well groups were analysed for geological and petrophysical variations (Table 1).



4 segments [-10,+20]

Fig. 9 *Unsupervised Vector Quantiser (UVQ) waveform segmentation into 4 segments.*

The UVQ analysis reveals that the percentage oil-bearing sands in segment 2 is significantly higher than simulated (39 and 66%, respectively). This implies that segment 2 is an indicator for oil provided the patterns are structurally conformable. Segment 4 collects only a few wells, which are characterised by a thick Dogger Beta with a hard acoustic response. This may be attributed to low porosity and/or carbonate cementation.

Table 1

	Original	Segment 1	Segment 2	Segment 3	Segment 4
Nr. wells	500	122	99	47	10
Av. thickness mu	15.1	16.0	10.3	19.4	21
Nr. mu.sand	5757	1054	774	677	163
Nr. mu.sand,Oil	2266	535	507	267	16
% oil sands	**39**	**35**	**66**	**39**	**10**
Av. density mu.sand	2250	2248	2237	2252	2263
Av. sonic mu.sand	252	254	260	252	245

Av=average, mu=middle unit, mu.sand=sand layer in middle unit, mu.sand,Oil= oil-filled sand in middle unit.

4. Conclusions

Neural network technology has matured in the past decade. The fear of using a 'black-box' is gradually replaced by an understanding that non-linear mapping techniques often perform better than classical methods. Many commercial software products on the market today offer neural networks as an engine to analyse geoscientific data. Because neural networks are easy to apply and the results often outperform alternative methods, the technology is rapidly moving from the research environment into the operational domain. With the need to find increasingly subtle relationships in ever increasing data volumes, the use of neural networks in seismic reservoir characterisation applications is expected to become even more popular in future.

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