PredictionPrediction of static and dynamic parameters from time-lapse 3-D seismic

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Introduction

Time-lapse measurements are used to determine the dynamic characteristics of an oil and/or gas reservoir. The time-lapse signal is interpreted in terms of pressure -, temperature - and water saturation changes in the reservoir. Changes are induced by production over time. In this paper we describe a method for predicting porosity and saturation at different seismic acquisition dates. We argue that we also need time-lapse seismic data for a proper prediction of porosity. The reason is the non-uniqueness of the seismic method. The same seismic response may belong to various combinations of static and dynamic parameters. With only one seismic measurement these parameters cannot be uncoupled. A change in seismic response caused by a change in saturation will thus result in an erroneous prediction of porosity. With two acquisitions it is feasible to invert both sets simultaneously. The inversion algorithm must learn to ignore variations in the two input sets to predict the static target parameter. A supervised neural network can do this.
Next we predict saturation at different seismic acquisition dates. Again we are facing the problem that porosity is coupled to saturation, but now we have the added advantage that porosity is known, i.e. was predicted in the previous step. We make use of this by including porosity as an input parameter in the saturation prediction workflow.

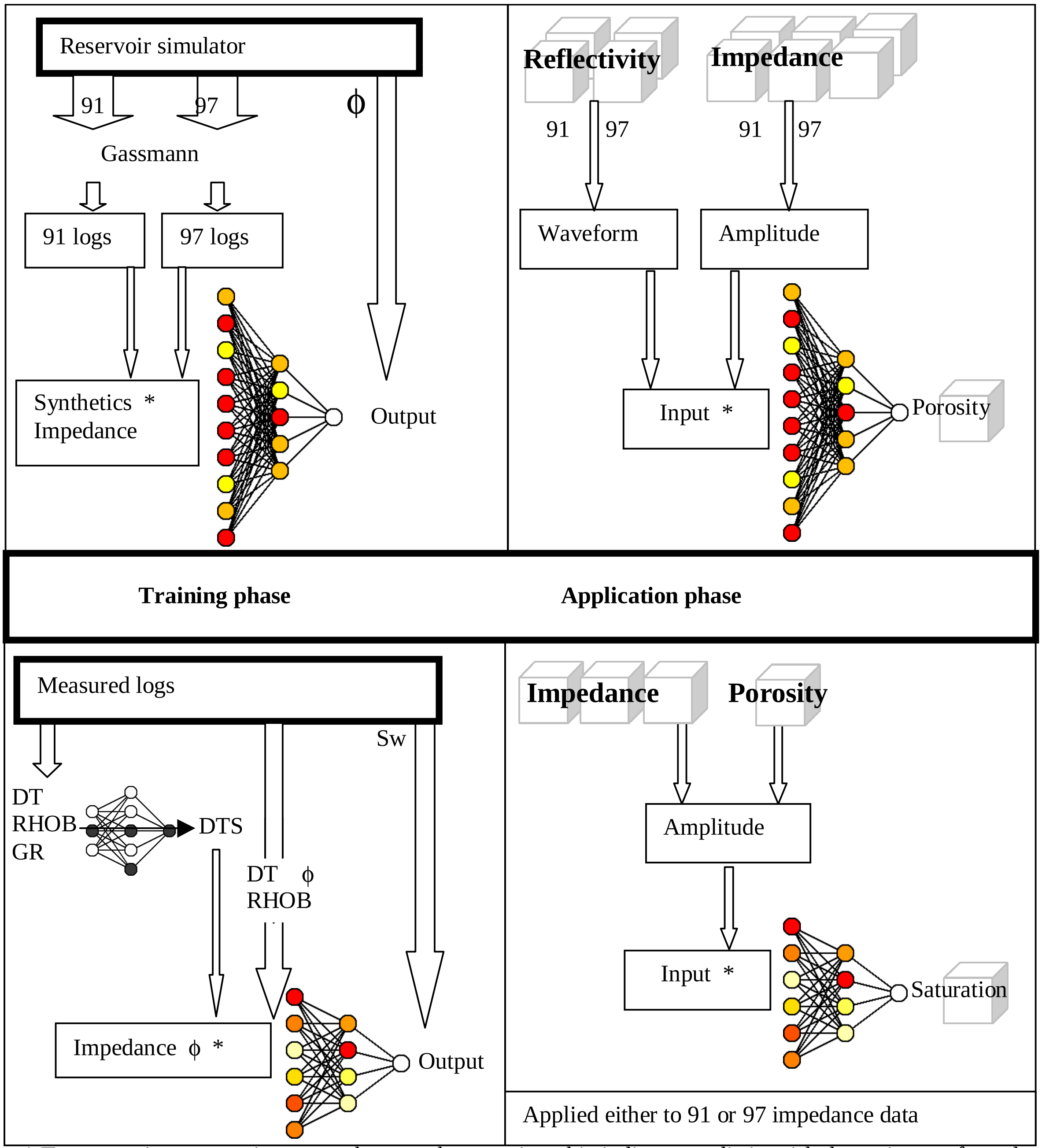
A real case study on the Statfjord field (Oldenziel, 2000) is used to describe the methodology.

Porosity prediction

The data set comprised of two seismic surveys, acquired in 1991 and 1997, respectively. Available were a/o partially stacked reflectivity cubes, inverted acoustic - and elastic impedance data cubes and time-equivalent logs. The latter were made with a modified Gassmann model using saturation curves at times 1991 and 1997 from the reservoir simulator. Shear sonic logs were in most cases predicted by a neural network from other logs.

Although porosity does not change over time, the seismic response does as a result of production. To avoid mapping production-induced changes to variations in porosity, all available seismic cubes from both acquisition times are used simultaneously to predict porosity (Fig. 1). At each sample position the complete waveform rather than some derived attributes is taken from the seismic reflectivity cubes. At the same position the amplitude is extracted from each of the impedance cubes.
Neural network examples were extracted from the time-equivalent logs of the real well database. To ensure full alignment over the target zone between input and target response, the input reflectivity waveforms and impedance values were derived from synthetic seismograms rather than from the real data volumes (de Groot, 1999). Two more inputs were fed to the neural network. The

reference time relative to the Top Brent horizon is given to model vertical porosity trends in the reservoir. The second input is an indicator to reflect the distinctly different structural styles in the field. The neural network was trained on examples derived from approx. 100 wells. Some wells were set aside and used to test the network's performance as blind test locations. The trained network was applied to a 150ms interval hanging from the top reservoir.



* Two more inputs are given to each network; a stratigraphic indicator to distinguish the main area from the East flank and the reference time, i.e. the stratigraphic time relative to top reservoir.

Fig. 1 *Flow diagram for porosity prediction (top) and water saturation prediction (bottom). Impedance means acoustic impedance, and mid - and far angle elastic impedance.*

The resulting porosity volume (Fig. 2) corresponds well with the actual knowledge of the Brent Group. The Tarbert and Etive Formations clearly show the highest porosity, while Lower Ness, Rannoch and Broom Formations show up as lower porosity units. Also shown in Fig. 2 is the result for one of the blind test wells.

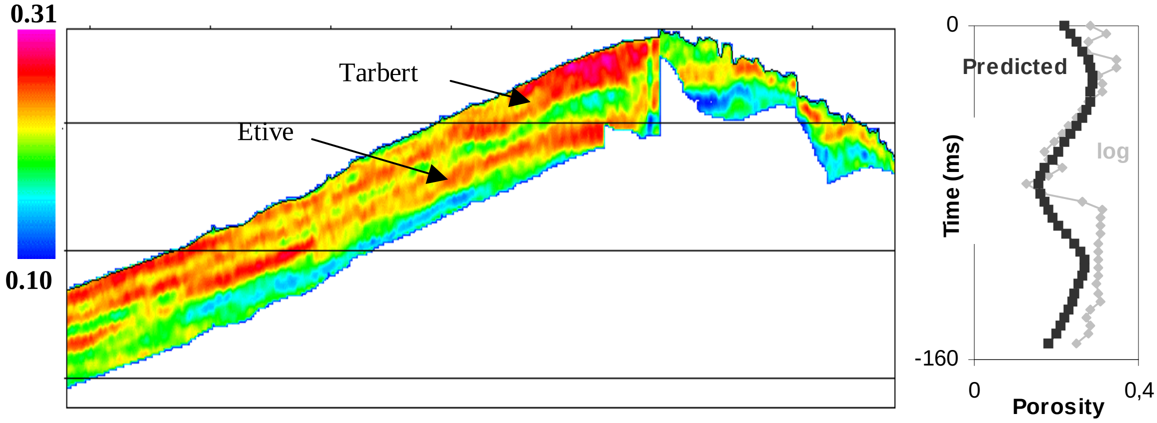


Fig. 2 *East-West profile through the porosity volume and a comparison between predicted and actual porosity at a blind test location.*

Water saturation prediction

Variations in time-lapse signals are expected to be larger in porous rocks than in less porous rocks for two reasons. Firstly, the effect of fluid replacement on the seismic response is more pronounced whit increasing porosity. Secondly, porosity is in general related to permeability. This implies that porous rocks are more easily drained than less porous rocks resulting in larger changes in saturation. The consequence of this reasoning is that porosity is a desired input for predicting saturation. Besides porosity, the acoustic and elastic impedance are also used to predict saturation (Fig. 1)

One neural network suffices to predict water saturation at different times. Applied to the 91 data set, the network predicts 91 water saturation, and applied to the 97 data set, it predicts 97 water saturation (Fig 1). This can be explained as follows. Each well has a set of measured and derived logs. Each set represents a consistent combination of inputs and target responses from which examples are extracted every 4ms over the entire target zone. The large set of measured logs in Statfjord covers the entire range of possible variations. Hence there is no need to expand the set with time-equivalent logs and/or simulating pseudo-wells. As was done with the porosity prediction the training set was constructed from approx. 100 wells with some wells set aside as blind test locations.

Fig. 3 shows the Southern part of the field. Slices are taken at 12ms below the mapped top reservoir. In the main part of the field the 91 saturation is generally much higher than in 97. At the right the difference between the 91 and 97 water saturation is shown, where the former is subtracted from the latter. Flooding with water is indicated in black. White or grey indicates respectively an increase in oil or no production at all. The difference plot reveals the overall level of depletion in the main area.

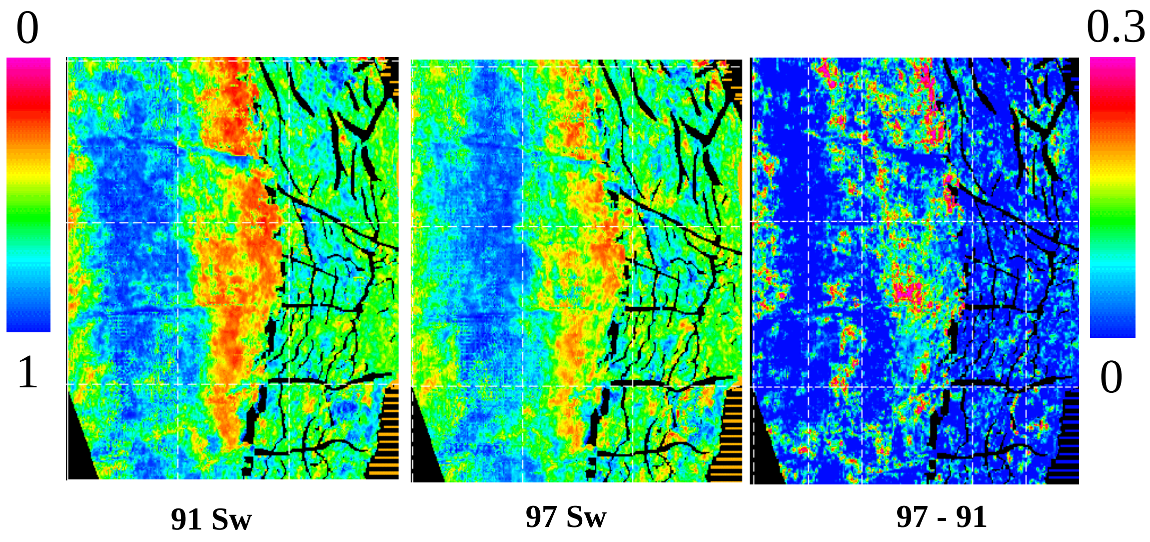


Fig. 3 *Slices at 12ms below top reservoir through 91 - and 97 water saturation volumes (left and middle, respectively). At right the difference (97 minus 91) is shown. Black indicates flooding with water.*

Conclusions

Time-lapse seismic gives an advantage over 3D seismic, in that it contains information on the dynamic behaviour of the reservoir. It also allows better estimation of static parameters such as porosity, because we can decouple the static and dynamic seismic imprints. Data from both acquisition times must be inverted simultaneously to predict the desired static parameter. This was demonstrated with a porosity prediction on Statfjord. The porosity neural network was trained on time-equivalent well data produced by the reservoir simulator and a modified Gassmann model. In a subsequent step the predicted porosity was used to predict saturation at the seismic acquisition times. Only one saturation neural network was trained on examples derived from measured well logs. Application of the trained network to the 1991 and 1997 impedance volumes yielded the desired saturation volumes.

Porosity and saturation predictions for the respective seismic acquisition dates confirmed the overall interpretation of the reservoir behaviour.

References

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