

Utilizing pseudo-wells on a sandstone reservoir in onshore Germany

Arnaud Huck^{1*} and Dr Tillmann Roth², demonstrate the use of pseudo wells for new applications.

Pseudo wells (1D stratigraphic columns with attached well logs) are realizations of wells that could be drilled within a study area and have found widespread use in reservoir characterisation today (de Groot et al., 1996; Oldenziel et al., 2002; Spikes and Dvorkin, 2004).

However, the use of pseudo-wells to date has been limited to improving data and better establishing relationships between seismic amplitudes, elastic parameters and rock properties. These relationships are primarily derived using statistical tools such as Bayesian classification and neural networks. Such workflows apply knowledge extracted from the larger database on the available seismic data following its inversion to elastic quantities using industry standard inversion methods (coloured inversion, model-based post-stack and pre-stack inversion, sparse spike etc.).

This inversion of seismic data into elastic parameters relies on the existence of a geological model that contains the low frequency part of the output elastic parameters, either during the inversion, or to be added subsequently. The rock property predictions from the elastic parameters carry all the uncertainties of the method used for the inversion to elastic parameters – to which one must add the uncertainties related to the prediction method itself.

Grant (2013) showed the large degree of uncertainty that is introduced into the geological model when relying on a well-based, interpolated, initial model. In such cases, the uncertainties are difficult to estimate, and at the same time, one also lacks an objective method to give the geophysicist a tool to choose one low frequency model from another.

The current method of choice is therefore to create the initial model without a well, invert the data, and use the log of that blind test well to measure the error introduced by the creation of the low frequency model. This method is very easy to perform, but has a large impact on the low frequency model itself when few wells are available to create it.

Indeed, in such cases the low frequency model will be highly variable depending on what well has been used as a blind test, especially if the wells have large variations in logs and stratigraphy. As a result, performing such a blind test analysis nearly always shows large errors, owing not only to

the poor performance of the inversion itself, but also because of the methods used to measure the error.

The emergence of the HitCube

A new utilisation of pseudo wells, however, seems to have emerged over the past few years – what is known as the HitCube method. The primary objective of the development of the HitCube is to overcome the intrinsic limitations of building a geological model by gridding the well logs. In essence the HitCube is a stochastic inversion method that is based on trace matching technology.

By matching the pseudo wells directly with the seismic waveform, the new method has proved its feasibility by mapping in three dimensions gas-filled channels (Ayeni et al., 2007). This new workflow uses the pseudo wells with the aim of predicting reservoir properties with uncertainties throughout a seismic cube, without using any a priori volume.

In this method a large number of pseudo-wells are generated through Monte Carlo Simulation (see Mardia et al., 1979; Deutsch and Journel, 1992; de Groot, 1995). Synthetic traces from these pseudo wells are matched with real traces at every sample position throughout the seismic volume. A 'Hit' exists when the correlation value between the modelled synthetic trace and the real seismic traces exceeds a defined threshold, i.e. the rock properties defined by both the model and real seismic traces are considered to be similar.

A number of hitting models are used to generate the rock property trace by stacking the property traces of these models. The method can work volumetrically like in channel mapping, or very locally in order to characterise an already delineated reservoir.

This second type of HitCube application recently showed how it can be used to map reservoir facies and impedance distribution in an unconventional shale gas play (Pierard et al., 2013), to predict a gradient impedance distribution in a deep marine turbidite field (Connolly et al., 2013), or even to estimate fluid contact movements from a 4D seismic survey (Huck et al., 2013).

In this article, we will further illustrate the capabilities of the current HitCube method on an onshore German

¹ dGB Earth Sciences.

² RWE Dea.

* Corresponding Author, E-mail: arnaud.huck@dgbes.com

Reservoir Geoscience and Engineering

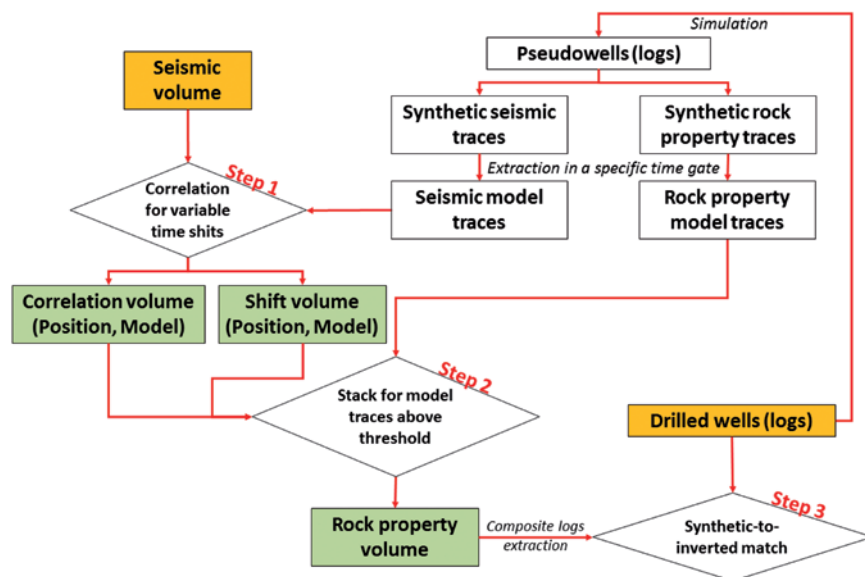


Figure 1 The HitCube workflow.

reservoir with the objective being to map the porosity distribution of a deep, sub-salt reservoir.

The reservoir quality from a Rotliegend sandstone reservoir was investigated using this procedure from a pre-stack depth migrated 3D seismic volume. The results were then tested against the well log data.

The application demonstrated the reliability of the inversion with a good cross-correlation of predicted and well data. A waveform segmentation study and petrophysical analysis conducted on the field confirmed the patterns and amplitudes that were extracted from the inverted volumes.

The workflow

A set of real wells is rarely statistically representative of the full area of interest, especially when the availability of well data is limited. The generation of a pseudo well, however, may overcome this problem.

In this analysis the real wells, geological knowledge, mathematical functions, correlations and statistical variations are used to generate plausible realizations of 1D stratigraphic columns and corresponding logs – the pseudo wells (de Groot, 1995). The HitCube algorithm was modified to enable a direct stochastic inversion to rock property volumes, such as porosity, without the need to create a low frequency model interpolated between the wells.

The algorithm

The HitCube algorithm matches the synthetic (model) traces with real traces throughout a seismic cube. The workflow is presented in Figure 1.

The seismic response at the reservoir level is extracted in a time window from the synthetic seismic and rock property traces of each pseudo well (see Figure 1, top right). This time window is called the matching window, since it defines

the length of the matching operator using to measure the fit between a given pseudo-well and the seismic trace.

Its length can be fixed, or made variable depending on the reservoir thickness in the pseudo-well. Pseudo-wells with a thick reservoir would thus use a larger matching window than pseudo-wells with a thin reservoir. This matching window is however always meant to be set larger than the reservoir thickness on both sides when matching seismic reflectivity in order to take into account the wavelet side lobes. However if the match is carried out on band-limited impedance traces, then the matching gate can be reduced.

The first step is to correlate the extracted synthetic seismic response to the traces in the volume using a sliding window called the search window. The synthetic seismic response from the pseudo-wells is extracted using a reference marker, most often the top reservoir.

In addition, the seismic response from the real traces must be extracted from a seismic interpretation. However, in many cases the reference marker in the wells does not match exactly a specific seismic event, peak, trough or zero-crossing. The search window is thus utilised to capture the time difference between the seismic interpretation and the reference marker.

The synthetic seismic response in the matching window is shifted up and down given the search window, and the match is measured every time the waveform is shifted by one sample down.

For each pseudo-well at each trace, several match values are computed corresponding to different shift values (delta). A search function is used to see if the match as a function of delta possesses a maximum within the search window. If this is not the case the pseudo-well is discarded. Otherwise the match for the optimum delta, and this optimum delta value, are retained and assigned to the pseudo-well. This provides a correlation

Reservoir Geoscience and Engineering

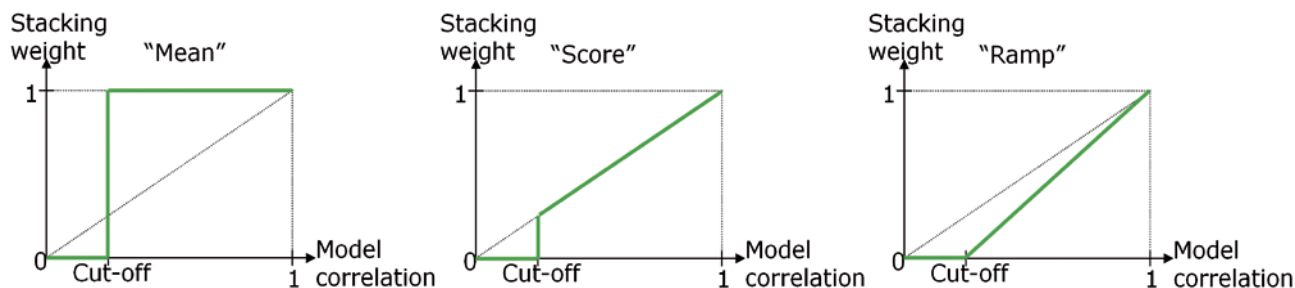


Figure 2 Stacking weight functions, as functions of the model correlation.

value for each trace per pseudo-well and the optimum time shift for the alignment of the pseudo-well with the real data.

The second step is to stack the rock property traces of the best fitting pseudo-wells, i.e. the models that have a correlation larger than a predefined threshold or cut-off value. All models above the threshold might be stacked or only a limited number of them, starting from the best fitting models. The stacking of the rock property traces is performed after applying the delta value – different for each pseudo-well. Several stacking methods may be used and are presented in Figure 2.

The stacking type ‘mean’ corresponds to the conventional stack, i.e. a summation followed by a normalisation. The two other stacking types give increasing weights to the best fitting models. The standard deviation of the input of the stack is also computed as a secondary product, in order to measure the uncertainty of the prediction as the variability in the pseudo-well rock properties.

The quality control of this workflow is illustrated in the third step (Figure 1) and consists in correlating the rock property traces of the real wells with the composite traces extracted from the inverted volume.

A case study, onshore Germany

The presented workflow was tested on a Rotliegend sandstone reservoir, onshore Germany. The seismic response at target level was variably affected by the presence of thick overlaying salt formations. A small part (73 km²) of the entire 3D pre-stack depth migrated seismic dataset was used. Twenty wells were available to appraise the field in and around the area covered by the seismic data and were used to generate statistics for the pseudo well modelling.

The sandstone reservoir is of good quality with an average porosity of 11%. The logs show a good correlation between impedance and total porosity (90%) and impedance vs. log permeability (80%) in the sandstone formation. dGB Earth Sciences’ pseudo-well simulator was used for the analyses and integration of well and geological information into a stratigraphic framework and for pseudo-well simulation.

The seismic data was spectrally blueed in order to boost attenuated amplitudes in the frequency range 35–50Hz (Blache-Fraser et al., 2004). 200 stochastic pseudo-well models were generated from this database (see Figure 3).

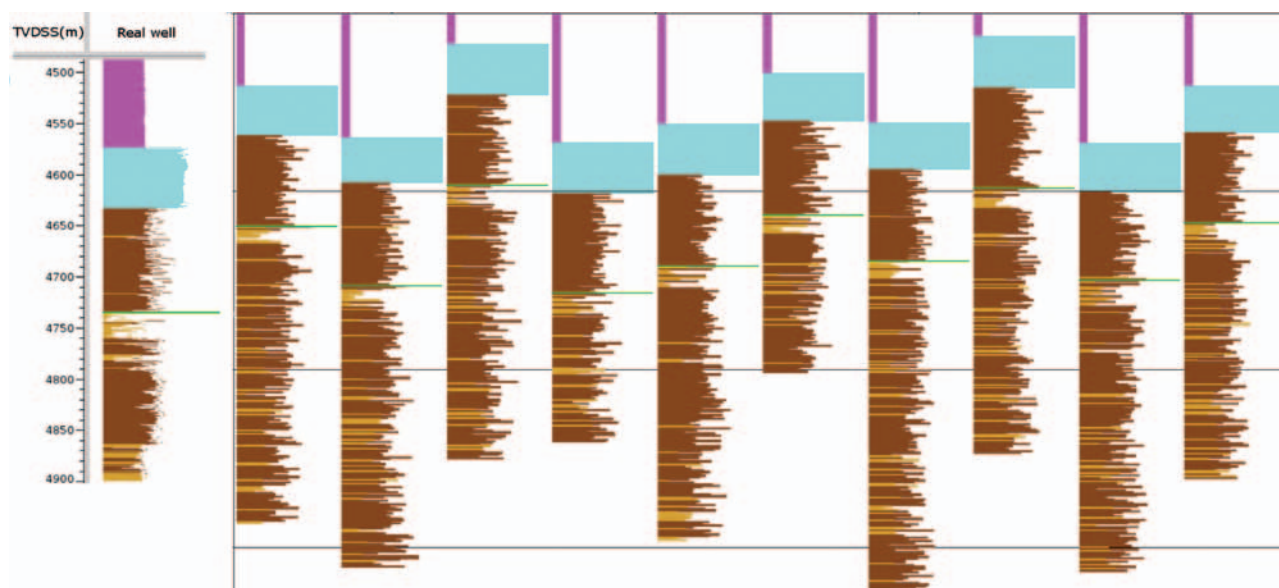


Figure 3 Impedance Logs of a Drilled Well (left) and 10 Pseudo-Wells (right). The colour indicates the lithology (sand=yellow; silt = brown; blue= anhydrite; pink= halite). Note that the real well shows its actual log, while the pseudo-wells are blocked at 1 m.

Reservoir Geoscience and Engineering

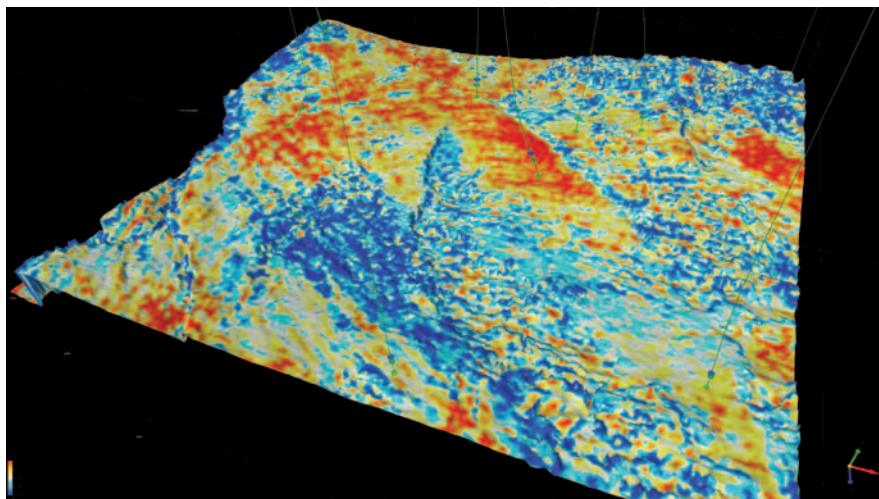


Figure 4 Average Total Porosity Map. The Well Positions are indicated by the deviated well tracks in green.

A composite deterministic wavelet was extracted by tying the existing wells and was used to compute the zero-offset synthetics of the pseudo-wells.

A scale-sensitive matching operator, measuring the similarity between real and synthetic traces, was used. The benefit of using such an operator is that it discriminates identical waveforms of different amplitudes (scaling). As a drawback the synthetic traces must be carefully scaled to the amplitudes of the seismic, especially when the stratigraphy is very uniform, and the lateral variability primarily consists of lateral rock property changes.

In such cases, the position of the loops in the waveform is rather stable, but the strength of the events vary because of the rock property changes. The scaling could be applied with confidence given the local geology. The base of the Zechstein salt creates a very strong reflection going from Zechstein anhydrites into Permian shales. This event could be correlated with confidence by extracting the event amplitude on both the synthetics and the seismic volume at the location of the wells. The regression between amplitudes of the synthetic event and amplitudes of the same event in the volume has a 99% cross-correlation, leaving little uncertainty on the scaling part of the workflow.

The correlation of the 200 models with the seismic data showed matched (similarity) between 67 and 99% and only small time shifts (between -4 and $+4$ ms) outside the fault and salt areas were detected. Only small shifts were expected since the contrast between the porous Wustrow reservoir and the overlaying shales generates a clear seismic event (local impedance decrease).

As a result, the mapped interpretation corresponds fairly well with the top reservoir marker. Correlation thresholds of 0.30, 0.50, 0.80, and 0.85 were tested when stacking the property traces. The maximum number of stacked traces varied from 1 to 50 in different tests, using all three stacking types.

It turned out that the maximum number of stacked traces is the most important parameter as it controls the amplitude distribution in the output volume. It must be realized that the HitCube stacking does not contain any on-the-fly scaling of the output rock properties during the stacking (second step).

Stacking just a few traces will preserve the dynamic of the variations of the resulting trace (high porosities in the reservoir and low porosities outside reservoir areas, for example). The disadvantage, however, is that when using a few traces, the lateral continuity of the output volume decreases. Too many input traces would on the contrary cause the stacking process to remove all detail from the individual models and return flat traces around the average rock property value.

For all tested output volumes the average porosity in the sandstone formation was computed along the well paths. This predicted average porosity was compared with the upscaled average porosities from the wells. The upscaling of the logs was performed during the depth-time conversion of the logs with an anti-alias filtering at 4 ms (the seismic sampling rate). This process is a mandatory step when comparing

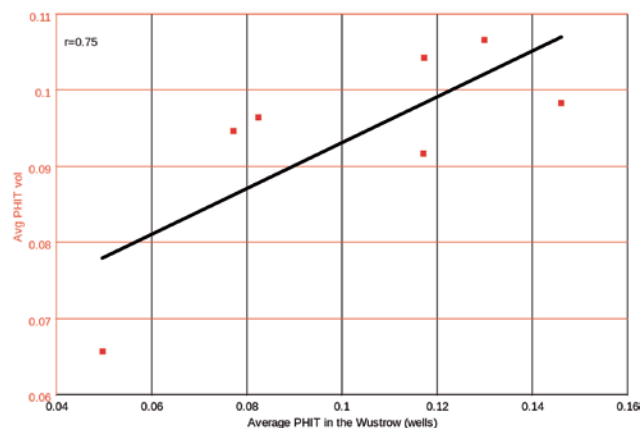


Figure 5 Average Total Porosity (Ratio) from the Upscaled Logs vs. Predicted Average Porosity.

Reservoir Geoscience and Engineering

the logs with inverted volumes of lower frequencies because of the band-limited nature of the seismic data.

The optimal porosity (Figure 4) volume was computed with a maximum number of stacked traces of 20 and a threshold of 0.80 for the correlation between seismic and modelled traces.

The threshold parameter is less important since only a maximum of 20 traces are stacked, but may have an influence on the number of stacked traces. The stacking method appeared to have only very minor influence on the output, since the output porosity distributions were all very similar. The 'ramp' and 'score' stacking yield virtually the same results – slightly better than with a conventional stacking (the correlation between well data and inversion output improves only by a few per cent). Correlation coefficients were extracted in order to quantify the prediction accuracy per test.

Figure 5 presents the correlation with the wells available within the seismic volume for the optimal set of processing parameters. It shows a good cross-correlation between real and predicted average porosity, although the predicted absolute range is slightly narrower than in the reality.

Discussion

It should be noted that the stacking part of the workflow does not make any distinction between the various frequencies of the target property. This is a major difference with traditional inversion methods, where the geological model is located in the initial model, while the detail – the high frequencies – is retrieved by the inversion of the seismic amplitudes.

In the HitCube approach, the geological model is located in the pseudo-well database rather than in a 3D volume. In other words the nature of the a priori is completely different: the geological model is represented by a petrophysical model, instead of originating from a geostatistical interpolation.

As a consequence, the task of creating the geological model running the inversion no longer only involves the geophysicist, but more and more the petrophysicist. That should lead into more robust models and predicted volumes, since the entire inversion workflow gets driven by geological principles, whereas the geophysical inversions methods are limited to the application phase, i.e. the trace matching and property stacking of the HitCube inversion itself.

Finally, the main limitation of using a well-based initial model no longer applies. None of the wells are used directly during the matching in order to predict the rock property distribution. As a result, they can all be used as an independent measure of the prediction error, for both the low frequencies and the frequencies within the seismic bandwidth. Again this was achieved because the method uses pseudo-wells, i.e. fake wells without spatial location, but that behave as an appropriate stochastic realization of a drilled well.

Conclusions

A workflow of stochastic inversion which inverts directly to rock properties using a pseudo-well database has been described. Its application to a real case study onshore demonstrated the reliability of the inversion with a good cross-correlation of predicted and well data. An independent unsupervised waveform segmentation study and petrophysical analysis performed on this field confirmed the patterns and amplitudes which can be extracted from the inverted volumes.

Acknowledgments

We would like to thank the RWE Dea, Wintershall, ExxonMobil, and GDF Suez consortium for supporting the development of this workflow and granting permission to publish this paper. Any conclusions or opinions expressed in this paper are solely those of the authors.

References

- Ayeni, G.O., Huck, A. and de Groot, P. [2007] The HIT Cube; matching Monte Carlo simulated pseudo-wells to seismic data for predictions with uncertainties. *69th EAGE Conference & Exhibition*, London.
- Blache-Fraser, G. and Neep, J. [2004] Increasing seismic resolution using spectral blueing and colored inversion: Cannonball field, Trinidad. *SEG International Exposition and 74th Annual Meeting*, Denver.
- Connolly, P. [2012] Seismic inversion in a geological Bayesian framework. *EAGE Integrated Reservoir Modelling Conference*, Abstract.
- Connolly, P.A. and Hughes, M.J. [2013] Inversion by trace matching. *75th EAGE Conference & Exhibition*, London.
- de Groot, P. [1995] *Seismic reservoir characterization employing factual and simulated wells*. PhD thesis, Delft University of Technology.
- de Groot, P., Bril, A.H., Floris, F.J. and Campbell, A.E. [1996] Monte Carlo simulation of wells. *Geophysics*, 61(3), 631–638.
- Deutsch, C.V. and Journel, A.G. [1992] *GSLIB Geostatistical Software Library and User's Guide*. Oxford University Press.
- Grant, S.R. [2013] The impact of low frequency models on reservoir property predictions. *75th EAGE Conference & Exhibition*, London.
- Huck, A. and Hicks, G. [2013] Using the 4D Hit Cube for seismic inversion in the North Sea's Blake Field. *World Oil* May 2013.
- Mardia, K.V., Kent, J.T. and Bibby, J.M. [1979] *Multivariate Analysis*. Academic Press, London.
- Oldenziel, T., Aminzadeh, F., de Groot, P. and Nielsen, S. [2002] Seismic reservoir characterization with limited well control. *7th International Meeting, Sociedade Brasileira de Geofisica* Abstract.
- Pierard, C., Jaglan, H., Rimaila, K., Huck, A., Brouwer, F., Jensen, S. and von Lunen, E. [2013] Unconventional shale gas reservoir characterization using the HitCube approach – mapping of Marl Rich mudflows in the Horn River Basin. *GeoConvention 2013 Calgary*, Abstract.
- Spikes, K.T. and Dvorkin, J.P. [2004] Reservoir and elastic property prediction away from well control. Online at www.rocksolidimages.com/pdf/Spikes_Dvorkin_04.pdf.