P063

Calibration of Simulator to Seismic Modeling for Quantitative 4D Seismic Interpretation

H. Amini* (Heriot-Watt University), C. MacBeth (Heriot-Watt University) & A. Shams (Heriot-Watt University)

SUMMARY

Realistic quantitative match between the results of simulator to seismic modelling and observed seismic can be used to update the reservoir model. For this purpose, it is vital to accurately adjust the parameters involved in petro-elastic model (PEM) and seismic modelling as the two controlling components of Sim2seis analysis. The PEM parameters are calibrated from a Sim2seis perspective using well log data. It is important to adapt the PEM parameters according to the lithology definition at the simulation cell scale, which is different from the log scale. The convolutional model (CM) is calibrated by comparison of the results with a full waveform pre-stack finite difference (FD) seismic modelling approach. The results show that if enough care is taken, CM can produce reliable results for 4D analysis. CM amplitudes are consistent with FD, while for time shift, in the case of small time shifts the error between the two methods can be of the same magnitude as the 4D signature.

Introduction

The ultimate aim of simulator to seismic (sim2seis) modelling studies is to update our understanding of the reservoir. This might consist of updating the static or dynamic components of the reservoir model. In general, simulator to seismic modelling is composed of two main parts: firstly the results of the fluid-flow simulation are converted to elastic properties through the petro-elastic model (PEM), and secondly, seismic modelling is employed to generate the synthetic seismic. To pursue our purpose of update through sim2seis, we need to limit the uncertainties from the modelling side such that the observed discrepancies between synthetic and observed seismic can be attributed only to parameters that need to be updated. In this study, we try to establish a best practice to calibrate the parameters involved in the modelling. Firstly we focus on calibration of the PEM parameters, and secondly we try to investigate the calibration of the popular convolutional model for seismic modelling by comparison of the results with a full waveform seismic modelling approach.

Petro-elastic model calibration

The calibrations are considered in the context of a field example. The field considered is located in the North Sea, and produces from a sequence of stacked turbidite channel sands. Early lithofacies studies by the operator identified three non-reservoir facies, and four for the reservoir. However from the sim2seis modelling perspective and the approach chosen to construct the latest reservoir model (Martin & MacDonald, 2010), it is necessary to revise the lithology definition – this affects the computation of the PEM parameters. Indeed, it is common for the flow simulation model not to retain detailed intra-cell knowledge of facies definitions, and only one set of saturation tables for the relative permeability curves is usually assigned to all sand types. Facies variations in the model are instead represented by introducing varying net to gross and k_v/k_h within the sand bodies. Therefore we attempt to characterize elastic properties of the reservoir by involving only sand and shale facies in our PEM analysis. We assign our PEM parameters by looking at the well-logs at the time of the base survey. Compressional and shear wave sonic, bulk density, gamma, and water saturation logs are used in these calculations.

In our approach, we firstly define a depth trend to the shale velocities and density. In doing this, we compensate each shale interval for the presence of sands. Next, we transform the well logs using inverse Gassmann to derive dry frame properties for the sand, and thus the MacBeth (2004) asymptote parameters for the sand stress sensitivity. To perform fluid substitution within the sand, we need to calibrate the dry sand mineral density, mineral bulk modulus, dry frame bulk and shear moduli. For mineral density ρ_m we use the following equation $\rho_m=(\rho_b-\varphi(\rho_w S_w+\rho_o(1-S_w)))/(1-\varphi)$, where ρ_b, φ, and S_w are replaced by their corresponding well logs. ρ_o and ρ_w are oil and water densities calculated using Black-Oil PVT data and the Batzle & Wang (1992) equations. However for bulk modulus in the Gassmann equation, two rock properties are involved which need to be calibrated: mineral and dry frame bulk modulus. Our analysis shows that the results are less sensitive to mineral bulk modulus compared to dry frame bulk modulus, and hence the former is set equal to 38 GPa (Meadows et al., 2005). In Gassmann's equations, porosity is replaced directly by the well log values, saturated shear and bulk moduli are calculated from sonic and density logs. Fluid bulk modulus is calculated again using Black-Oil PVT data and Batzle & Wang (1992) equations. The initial pore pressure profile is extracted from simulation model at the time of the base survey. Thus, with the dry frame moduli, we can also calibrate the sand stress sensitivity curves as we know the effective pressure. From our final calculations we can now assign a dry frame density of $2680\ Kg/m^3$, and asymptote bulk and shear moduli to *7.6 GPa* and *5.1 GPa* respectively.

Using the calibrated parameters for the sand and extracted shale trends, we perform fluid substitution followed by Backus averaging to mix sand and shale in each cell within the simulation model. Finally by employing the convolutional model we use the PEM results along with an estimated wavelet from the well-tie to generate the synthetic seismic cubes (Figure 1). From visual inspection the approach is seen to work well. However in-depth analysis shows that it cannot represent the full-range of variation in lithology and recover the exact contrast between sand and shale intervals. Figure 2 shows the histogram of calculated parameters versus log data. In all cases, especially for the velocities, the range of predicted values is narrower than the log data and hence the synthetic reflectivities are underestimated. Analysis shows that incorporating additional facies in the model may be one solution to this mismatch.

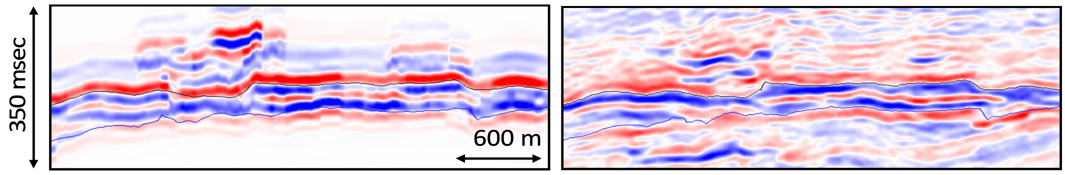

Figure 1 Sim2Seis results (left) versus observed (right) seismic after PEM calibration.

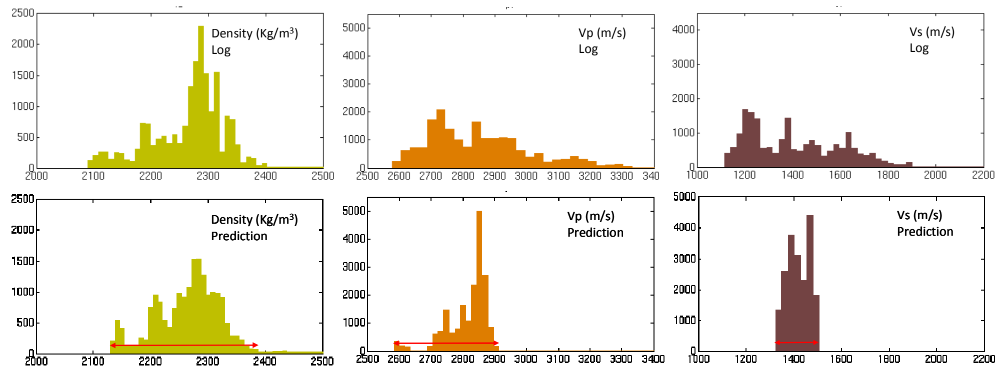

Figure 2 Well log data (top) versus the predicted velocities and densities from the PEM (bottom).

Seismic modelling calibration

Convolutional modelling is the most widely used method for the simulator to seismic modelling studies. Although many studies have compared different seismic modelling methods in sim2seis (Burnes et al., 2002, Thore, 2006) they are mainly visual and a quantitative comparison is missed in the literature. To check the reliability of convolutional modelling independent from PEM, we use a fixed PEM to generate synthetic seismic using two different approaches. The results from 2D elastic full waveform finite-difference (FD) modelling that inherits most of the features of wave propagation are compared to the 1D convolution approach. This study allows us to have a good understanding and control over different parameters of seismic modelling using the convolutional model. In the sim2seis procedure, it is important to incorporate details of the geometry of the seismic survey. After generating PEM results on the simulation grid, we extracted a 2D section to perform our seismic modelling. As our FD modelling uses a uniform cubic grid, we need to convert the original corner point geometry to a Cartesian grid. After this conversion, we design a typical marine survey, then generate pre-stack data accordingly and process it using ProMax to get the final reservoir image for both the base and the monitor surveys.

Figure 3(a) is the 1D convolutional modelling image; it reflects exactly the structure of the simulation model. All the lateral discontinuities in the events come from the fact that the simulation model is discontinuous in those positions. Figure 3(b) shows the image from FD modelling. Although this image is smoother because of the effect of the Fresnel zone, the level of the details is more or less the same as the convolutional image. To emphasise the need for calibration of the convolutional model using the geometry of seismic survey, first we calculated the difference between the zero-offset convolution and FD seismic image (Figure 3(d)). The strong effect of AVO can clearly be seen in locations with high difference values.

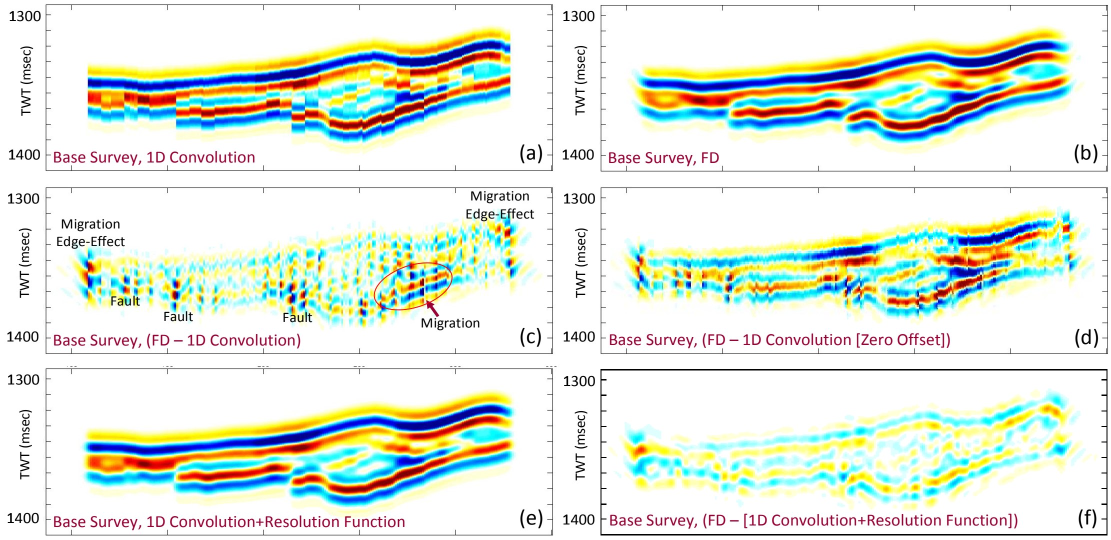

Figure 3 **(a)** 1D convolutional modelling **(b)** FD modelling **(c)** FD – 1D convolutional modelling **(d)** (FD (full offset) – 1D convolutional modelling (zero-offset) **(e)** 1D convolutional modelling + resolution function **(f)** FD – [1D convolutional modelling+resolution function]. To highlight the differences amplitudes are multiplied by a factor of 2 in figures **(c)**, **(d)**, and **(f)**.

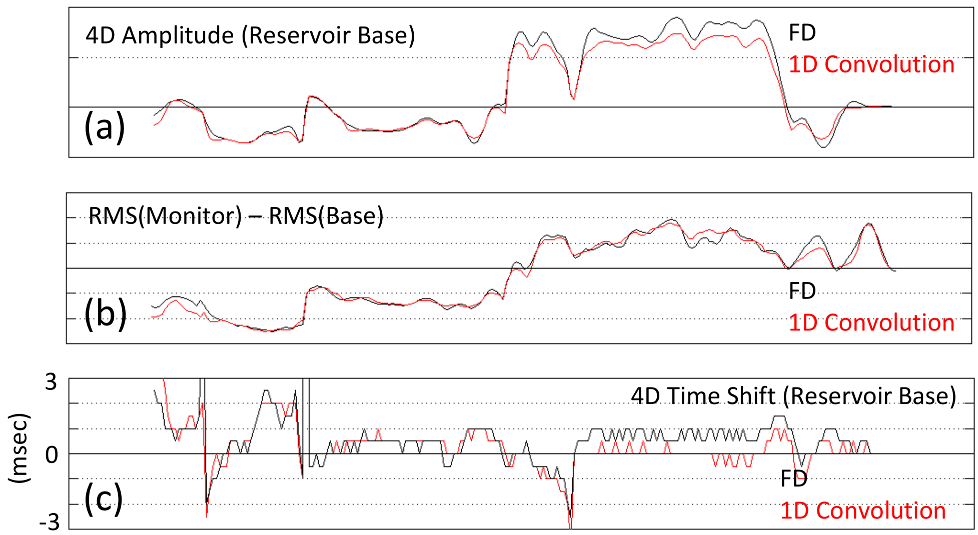

Figure 4 4D analysis of the seismic modelling. **(a)** 4D amplitude along the base of the reservoir. **(b)** 4D RMS amplitude. **(c)** 4D time shift at the base of the reservoir.

After including the offset values associated with each CMP, the difference decreases (Figure 3(c)). However, some differences are clearly visible at fault positions because the imaging operator is not included in the convolutional modelling. After taking the resolution function into account (Chen & Schuster, 1999), the resemblance between the resulting image (Figure 3(e)) and FD image (Figure 3(b)) is excellent. By looking at the difference section (Figure 3(f)) we can see that the differences that have been observed earlier are reduced to a lower level. Figure 4 shows the 4D analysis of the seismic modelling. Figure 4(a) shows the 4D amplitude along the base of the reservoir. The agreement between the two methods is good and the amplitudes in the convolutional modelling appear reliable. Figure 4(b) shows the difference between the RMS amplitude of the monitor and base surveys. The attribute is calculated between top and base of the reservoir. This shows a high degree of similarity between the modelling approaches due to averaging and disregard of the timing of the signal in forming the attribute. Figure 4(c) shows the 4D time shift at base of the reservoir. The error between the two methods for time shift calculation can be at the same level as the 4D time shifts themselves. This means that in our case, when dealing with rather small 4D time shifts it is difficult to model the observed 4D time shifts exactly.

Discussion and conclusions

Accurate adjustment of the parameters in sim2seis is vital to get a realistic quantitative match between the synthetic and observed seismic. We use well logs to adjust the PEM rock parameters to in-situ conditions. For this, it is important to adapt the PEM parameters according to the lithology definition at the simulation cell scale, which is different from the log scale. Our results show that if enough care is taken 1D convolutional modelling can produce reliable results for 4D analysis. This requires the use of a calibrated wavelet, and takes into account the geometry of the survey which will affect the illumination and AVO. To bring the convolutional modelling seismic image to the same level of detail as the observed seismic and compensate for the migration operator, imaging calibration via the resolution function is necessary. Seismic spatial sampling, migration aperture, and horizontal size of the simulation grid cells are factors which determine the horizontal resolution limit of the sim2seis results. Our results show that although 1D convolution amplitudes compared to FD are reliable, in the case of small time shifts the error between the two methods can be of the same magnitude as the 4D signature. Finally, the reliability of the above results needs to be checked for the presence of heterogeneous overburden and non-uniform survey geometry (Domes et al., 2009).

Acknowledgements

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