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Towards an Effective Petroelastic Model for Simulator to Seismic Studies

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SUMMARY

One of the major objectives for 4D seismic studies is to quantify pressure and saturation changes in the reservoir. A key ingredient of this interpretation is the petroelastic model (PEM), which links fluid saturations and pore pressure changes to the elastic property changes required for seismic modelling, time-lapse feasibility studies, 4D inversion and also seismic history matching. In this work we study the use of four different deterministic PEMs for simulator to seismic modelling. The models are calibrated to field data from a UKCS and Norwegian Sea with distinctly different geological settings. We find that there is no best choice of PEM, any may suffice, and that the number of input parameters for each is unnecessarily high. An alternate model for simulator to seismic modelling is suggested which uses only two parameters without loss of accuracy when predicting the mapped seismic response.

Introduction

The petroelastic model (PEM) is an essential cornerstone of quantitative 4D seismic interpretation. This model links fluid saturations and pore pressure changes in the reservoir rock to the elastic property changes required for seismic modelling, time-lapse feasibility studies, 4D inversion and also seismic history matching (Falcone et al. 2004). Numerous past studies have now pointed to the limitations and uncertainties that can exist within current models, also the difficulty of selecting an appropriate model and the need to calibrate to the *in situ* response (for example, Amini 2014). To address the latter two issues in particular, here we study the use of four different deterministic PEMs for simulator to seismic modelling. These models are applied to two fields in the UKCS and Norwegian Sea with distinctly different geological settings. For each model, the static rock frame components are calibrated using a range of wireline log data acquired prior to production. The dependence on pressure change is then added using coefficients derived from the laboratory. Based on comparisons across field and model, the number of parameters, degree of utility, and overall accuracy of the PEMs, conclusions are drawn on their effectiveness for 4D seismic interpretation guided by simulator to seismic modelling.

Description of models

As our ultimate end-goal is simulator to seismic modelling for the reservoir prior and then after production and recovery. The PEM models selected for the study are therefore influenced by the choices made when building the cellular fluid simulation model and its subsequent predictions. For our two chosen fields each model cell is specified by a net-to-gross *NTG* (or volume of shale V_{shale} = 1-*NTG*). This therefore assumes that facies variations for these reservoirs can be represented by only variations in the sand/shale fraction. This is true of the reservoirs used in our study but may not of course be fully representative of all reservoirs, and for the most general case PEMs may need to be constructed for each distinct lithofacies (Alfred et al. 2008). Our PEMs consist of two parts: first the static rock components by which the saturated rock frame moduli and density in their initial state are specified, and secondly the dynamic component which is defined by the fluid substitution model, effect of pressure changes on each fluid phase, and finally the stress dependency of the rock frame density and moduli. For the purpose of our study, four different recipes described here as models A, B, C and D, are used to build the static component that is then calibrated directly by the wireline logs. All models employ some aspects in common: Gassmann fluid substitution equations and semi-empirical relations for reservoir fluid properties (Batzle and Wang 1992). Also in common is the volume averaging of the solid and liquid phases for calculation of the density, and Voigt-Reuss-Hill averaging of the mixing of sand and shale mineral moduli. PEMs A, B and C use MacBeth (2004) for the stress-sensitivity, modified for log calibration. Assuming isotropic loading, the stress-dependent moduli are

$$\mu_{dry} = \mu_{dry\_\log}\left(\frac{1+E_\mu e^{-P_{res\_eff}/P_\mu}}{1+E_\mu e^{-P_{eff}/P_\mu}}\right) \qquad K_{dry} = K_{dry\_\log}\left(\frac{1+E_K e^{-P_{res\_eff}/P_K}}{1+E_K e^{-P_{eff}/P_K}}\right) \tag{1}$$

where E_K, P_K, E_μ and P_μ are the rock stress sensitivity constants estimate from a selection of core measurements (MacBeth 2004), P_{res_eff} is the initial effective pressure of the reservoir at pre-production time, and P_{eff} is the effective isotropic stress at the monitor survey time. For PEM D, the rock-frame stress-sensitivity is specified using the Hertz-Mindlin theory (Mavko et al. 2009).

The main difference between models A, B, C and D lies in the modelling of the dry frame bulk and shear moduli, K_{dry} and μ_{dry}, in terms of the corresponding mineral moduli K_{min} and μ_{min}, porosity ϕ, and volume of shale V_{shale}. Thus, PEM A follows Lee (2005) by specifying $K_{dry} = K_{min}\,(1-\phi)/(1+\alpha\phi)$ and $\mu_{dry} = \mu_{min}\,(1-\phi)/(1+\alpha\phi)$, where α is a consolidation factor $\alpha = aV_{sand} + bV_{shale} + c\phi$ lying in the approximate range $2< \alpha <20$, *a*, *b* and *c* are coefficients to be determined. PEM B follows the concept of critical porosity ϕ_c (Nur 1998, Mavko et al. 2009) to specify the dry rock frame according to $K_{dry}= K_{min}\,(1- \phi/\phi_c)$ and $\mu_{dry} = \mu_{min}\,(1- \phi/\phi_c)$, where our clastic fields ϕ_c lies between 36 and 40%. PEM C is based on Krief et al. (1990) model, which describes $K_{dry} = K_{min}\,(1-\phi)^{m(\phi)}$ and $\mu_{dry} = \mu_{min}\,(1-\phi)^{m(\phi)}$

where m(ϕ) = 3/(1- ϕ). Finally, PEM D is based on the intermediate stiff-sand model (Mavko et al. 2009) determined by the functional form of the soft sand model with Hertz-Mindlin contact theory taking the pressure effect into account and the modified Hashin-Shtrikman lower bound to obtain the dry frame moduli which consider the porosity dependence.

Application to field data

Use of the PEMs A, B C and D above comes with the cost of many free parameters to be constrained for the particular dataset. These parameters are determined using an optimisation algorithm to fit each model to the sonic, shear, and density logs (after careful editing and petrophysical evaluation). For each field, the optimisation is performed for the entire depth interval that intersects the simulation model, for a range of wells and also for individual segments of the logs sampling similar geology. For the UKCS field, data from five wells are considered, with two of the logs subdivided to give a total of seven segments to match. For the Norwegian Sea field, logs from three wells are divided to obtain a total of six log segments. Figure 1 shows an example of log prediction from the optimisation algorithm for both study fields, with the corresponding model parameters given in Table 1. In general, prediction errors for the UKCS field are less than 5%, 3% and 1% for V_P, V_S and ρ respectively. For the Norwegian Sea field corresponding velocity errors are a slightly higher 8% due to geological heterogeneity, but density prediction error is still less than 1%.

Field	PEM paradigm	Scenario	K_{sand} (GPa)	K_{shale} (GPa)	μ_{sand} (GPa)	μ_{shale} (GPa)	ρ_{sand} (g/cc)	ρ_{shale} (g/cc)
UKCS	PEM A	1	24	15	20	4	2.718	2.403
	PEM B	2	33	14	28	4	2.722	2.407
Norne	PEM A	1	23	22	16	12	2.689	2.635
	PEM B	2	29	16	25	7	2.728	2.637

Table 1 *Example of parameters obtained from model fit to the logs.*

PEM	Elastic Moduli	Coefficient of Variation (CV) UKCS	Coefficient of Variation (CV) Norne
PEM A	K_{sand}	0.1525	0.1699
	G_{sand}	0.2483	0.1521
	K_{shale}	0.1022	0.2699
	G_{shale}	0.1715	0.2806
PEM B	K_{sand}	0.0333	0.0751
	G_{sand}	0.0980	0.0589
	K_{shale}	0.1544	0.0882
	G_{shale}	0.2296	0.1422
PEM C	K_{sand}	0.0266	0.0741
	G_{sand}	0.1443	0.0564
	K_{shale}	0.1854	0.0869
	G_{shale}	0.3534	0.1322
PEM D	K_{sand}	-	-
	G_{sand}	0.0564	0.0634
	K_{shale}	0.4318	0.1606
	G_{shale}	0.3212	0.1378

Table 2 *Coefficients of variation for the input parameters obtained from log calibration.*

The exercise of parameter optimisation yields estimates for a variety of different logs segments. To make a comparison between the models, the coefficient of variation (sample standard deviation divided by sample mean) is calculated for each field and model parameter (Table 2). Values range from 0.03 to 0.3, indicating a reasonable overall consistency between fits laterally across the field and with depth. As might be anticipated, the shear moduli are observed to be more variable than the bulk moduli, and the shale parameters are more variable than those for sand, which agrees with the literature. Interestingly however, no model shows a particularly strong tendency of either low or high dispersion. We conclude from our analysis that no model can in fact be considered as the best. After the statistical analysis, each

set of estimated input parameters are now used in simulator to seismic modelling. Thus, each cell in the flow simulation model specified by a particular V_{shale} and ϕ together with saturation and pressure changes can be transformed into a corresponding V_P, V_S, and ρ. Figure 2 shows the resultant impedance change maps for producing units in either field. The log calibration deals with the dry fame characterisation in the static domain and impacts the amplitudes via Gassmann fluid substitution but it will not impact strongly on the pressure sensitivity.

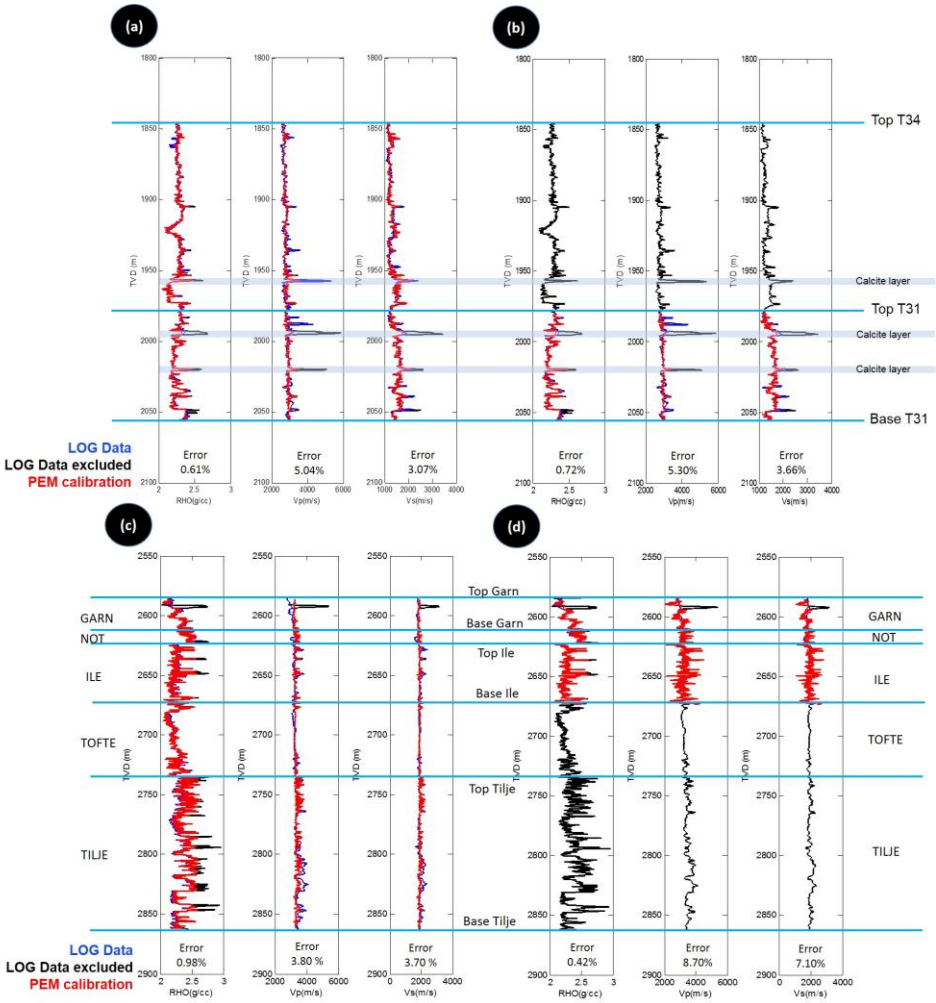

Figure 1 *Example of fit of PEMs to log segments from the fields of interest in our study. UKCS field: (a) PEM A for entire log segment, (b) PEM B only for the lower sands. Norwegian Sea field: (c) PEM A for an entire log segment and (d) PEM B only for the top sands.*

Discussion

For each PEM a large number of free parameters are required to be determined by the log optimisation procedure (9, 7, 6 and 8 for PEMs A, B, C and D respectively), plus four lab coefficients in common for PEM A, B and C as they share the same stress sensitivity model. Despite the data points available with which to calibrate effectively and the adequate degree of fit to almost all log segments, such models still however carry significant non-uniqueness which makes 4D seismic interpretation less intuitive. For time-lapse seismic maps in particular, it has been suggested that the main response may be captured by a simple two parameter equation $\Delta A = C_S \Delta S_w - C_P \Delta P$, where C_S and C_P are now the PEM parameters, which provide the balance between the relative contributions of saturation ΔS_w and pore pressure ΔP change to the time-lapse seismic signature ΔA (Alvarez and MacBeth 2013).

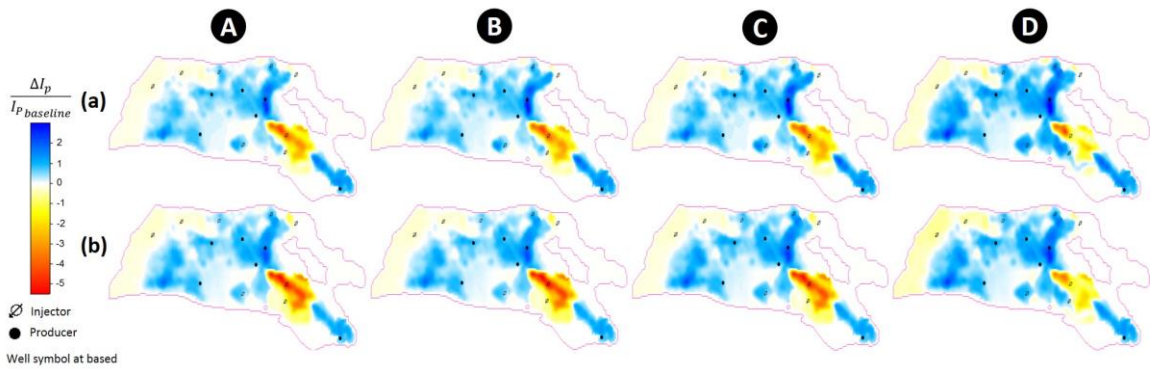

Figure 2 *(a) Maps of impedance change predicted by calibrated PEMs A, B, C and D for our UKCS field. (b) As in (a), but maps of impedance change predicted using our reduced-parameter model.*

Whilst this approach provides a framework that maps intuitive feel to a mathematical model, to be useful it still needs to be calibrated and linked to the simulation model. The calibration of the different PEMs above shows how this can be done. Based on our results, it is possible to select any of the PEMs A, B, C or D, and perform a calibration. After this, model predictions are directly inspected to yield the required C_P and C_S parameters. It is found that the two-parameter model is sufficiently close to the model results to replicate most of the 4D seismic response (see Figure 2).

Conclusions

There are numerous PEM choices available for 4D seismic studies. Our results suggest that all may be adequately calibrated to wireline log data for interpretation purposes, probably as a consequence of the high number of available free parameters. Indeed, the choice of a 'best' model appears not to be possible, as all provide a satisfactory match to the two field datasets considered in this study. When working with maps of 4D seismic attributes in particular, a good practical alternative is a two-parameter model linear in the pressure and saturation changes. It has been demonstrated that this must still however be referenced to the full PEM. Thus simulator to seismic modeling may incorporate a single generic model with parameters linked directly back to the PEMs and data.

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