Seismic history matching in the UKCS Schiehallion field

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Introduction
Reservoir managers would like to know the current state of their field and be able to see into the future to know how it will change. The former requires information about current fluid sweep and pressure change while the latter requires accurate reservoir description and a predictive tool such as a simulation model. Important decisions can then be made regarding facility maintenance and well optimization, but more importantly, unswept areas can be identified and new wells drilled.

Conventionally, simulation models have been used to determine the possible reservoir state and predict its behaviour. The modelling commonly begins with the geologist who creates a number of static geomodels, often constrained to the core data and the petrophysicist’s well log data in addition to the geophysicist’s pre-production 2D or 3D seismic. The upscaled models are then modified by an engineer so that they match static and dynamic well data, including fluid production rates and local pressures. Because the wells are widely spaced, many possible solutions exist where the well data will match. Time-lapse (4D) seismic can reduce the non-uniqueness by identifying changes in fluid saturation and/or pressures. This information is now available in qualitative form almost routinely in a number of North Sea and Gulf of Mexico fields, but the goal is to integrate this data quantitatively with the modelling process together with other available data.

To achieve this goal, we have developed an automated history matching method to include as much reservoir data as is necessary and sufficient, including core and well logs, seismic, production data, SCAL, etc. Here, we apply our method to the Schiehallion UKCS reservoir where we update the operator’s model using geostatistical approaches and obtain an improved match to seismic and a good match to production data. Finally, the uncertainty of the parameters and predicted behaviour is analysed.

Method
The details of our method (Figure 1) may be found in Stephen et al., 2005. We generate multiple flow simulations simultaneously using a suitable parameterization of the reservoir description. These models are converted to predicted seismic and well behaviour and compared to the observed data using a misfit. Parameters are then chosen by subdividing the parameter space around a number of the best models and the forward modelling process is carried out again. Each iterative step is repeated until sufficient models have been generated, possibly numbering hundreds or thousands.

Generation of multiple models
Simulation models may contain tens of thousands of cells with 10 or 20 times as many unknown parameters. Geostatistical methods reduce the dimensionality of the parameter space by many orders of magnitude such that the model depends on global statistics describing spatial distributions of parameters and how they are inter-related. The reduced parameter space typically includes correlation lengths for each variable (e.g., porosity, permeability, net:gross) as well as parameters describing inter-relationships (e.g., porosity – permeability relationships).

The Pilot Point method with Kriging is based on such a method. A set of Pilot Points are chosen in the simulation grid either as single cells, or as columns, and property values are controlled as part of the history matching. The points are effectively treated as a set of pseudo wells so that properties between them are varied by interpolation or, in this case, Kriging. We use this method to update a permeability distribution via a set of multipliers. We also modify fault properties by varying their transmissibility multipliers. These vary as fault segments, which may be grouped appropriately to...
reduce parameter numbers. Fault locations are very difficult to determine as part of an automated scheme, however, and should be defined during the model building process.

Comparison of seismic data and the reservoir model
We calculate the predicted seismic impedance for each cell in the simulation model using a petroelastic model together with fluid saturations and pressures from the simulations (e.g., MacBeth et al., 2005). We obtain the bulk modulus using Gassman’s Equation to capture the saturation effect while the pressure effect is represented in the dry bulk modulus via an empirical relationship (MacBeth, 2004). The parameters of our petro-elastic transform are also included in the history matching scheme.

To compare predicted impedances with observed seismic, both properties are transformed to represent the same volume because the predicted impedance represents flat, thin bins (typically 100 m x 100 m x 4 m) relative to those of observed data, which are cubic (25 m x 25 m x 25 m in our study). The predicted impedances are converted to a map by vertical upscaling and then downscaled onto the seismic grid with distance-weighted interpolation. If the observed data does not represent absolute impedance, then, for comparison, we normalize observed and predicted surveys to their pre-production mean and standard deviation before comparison.

A misfit function is used to compare each observed variable with its predicted equivalent, including both seismic data and conventional production data from wells. While we generally allow for correlation of the data errors, we find that for the Schiehallion dataset they are largely uncorrelated. This reduces the misfit to a sum of squares properly weighted by the data error, and these are summed for all models.

Uncertainty analysis
Using Bayes Theory, the misfits provide the conditional likelihood of each model for the given data and these are used to update prior model probabilities. The updated probabilities may be resampled using Markov Chain Monte Carlo methods as part of the uncertainty analysis of the unknown parameters giving a set of probability distributions for each. These probabilities can also be used as weights to determine the ensemble average and spread of variables, such as saturation or pressure in each cell, when predicting long term reservoir behaviour. Since we refine the parameter space near most likely models, a simple average may be approximated as an equally weighted average over the ensemble.

Results
Reservoir properties
Our data set consists of two P-wave seismic volumes, migrated stack and coloured inversion stack (e.g., Lancaster and Whitcombe, 2000), collected for three surveys, gathered in 1993, 1999, and 2000. Production started in 1998. The migrated stack was cross-equalized and calibrated by the
operator who also transformed it by combination of phase rotation and filtering, to give the coloured inversion stack, a pseudo relative impedance. Using the operator’s time to depth conversion and the location of the reservoir horizon, we generate attribute maps for each survey by integrating over suitable time windows. We create a map of the root mean square (RMS) of amplitudes of the migrated stack and at pre-production (Figure 2a), this correlates with reservoir quality, i.e. net:gross, as is generally found in thin reservoirs and particularly here (Leach et al., 1999). We also create maps (Figure 2b-c) of the time-lapse difference of the sum of negative values of the coloured inversion of each survey, which we use as a pseudo-impedance difference.

The time-lapse signature (Figure 2b and c) largely follows expected behaviour at the wells with softening occurring at the injectors while gas evolution may cause softening at the producers. I2 is only active in the first year, and the seismic shows stiffening in the second year as the pressure relaxes to equilibrium. Producer P1 is inactive in the first year, and the anomaly nearby (Figure 2b) is attributed to a shadowing effect from an active layer above this sector (see Ch.6, Soldo, 2005). Water saturation effects are not obvious here though reservoir water induced stiffening is seen at wells elsewhere in the reservoir (Saxby, 2001).

Finally, the 4D attribute map (Figure 2b) appears to oscillate between positive and negative values rapidly over just a few hundred metres. This dynamic effect can be attributed to noise in the generation of the 4D seismic. It occurs in areas where saturation changes are unlikely and over a scale where pressure should decrease from injector to producer (for example, mid-way between injectors I2 and I3). Visual inspection suggests that this variation coincides with changes in the RMS amplitude of the migrated stack. However, we see stiffening where the latter is low but softening where it is high. It is possible that the pressure response is lithologically dependent. Increased pore pressure in the sand may squeeze the shales so that they stiffen. Figure 3 shows a cross plot of 4D signature against the RMS amplitude of the migrated stack for each bin where the model predicts pore pressure increases. There appear to be separate populations depending on the magnitude and direction of the pressure change.

Base case model performance
The base case model simulation model, supplied by the field operator, yields grid cell pressures that qualitatively agree with the seismic response in the reservoir (see Stephen et al., 2005). Its predicted impedances were obtained using the petro-elastic model with parameters derived for the field area (MacBeth, 2004) and the 4D signature compares poorly to the observed data. The baseline predicted impedance (Figure 4a) is quite different from the observed RMS amplitude of the migrated stack suggesting that the bulk net:gross is too high, particularly around the injectors I2 and I3. From the predicted difference of impedance (Figure 4b), it appears that the pressure build up in the model is under-predicted and the presence of more sand leads to a dominant saturation effect.

History matching
The history matching is performed in two stages. First, the static pore volume is updated for each cell so that predictions of the pre-production impedance variations closely resemble the RMS amplitudes of the migrated stack. We alter the pore volume by varying net:gross (i.e. ratio of sand to shale, the latter with zero pore volume) only because the operator interpreted that the sand possesses nearly uniform porosity. The RMS amplitudes of the migrated stack are transformed...
into a map of average net:gross for the reservoir and a new 3D distribution of net:gross is created using simulated annealing. For details see Stephen et al., 2005. Although the misfit is reduced, the new model is now much too pressure dominated by some combination of the pressure itself or its effect on seismic.

In the second stage, fault transmissibilities, permeabilities, and the pressure response of the petro-elastic model are updated via history matching to dynamic data. The total number of fault segments is quite high so these are grouped (Figure 5) and the transmissibility is changed using a single scalar for each group. Permeabilities were updated using a Pilot Point method (e.g. Stephen et al., 2005) with Kriging (Figure 6). Seismic pressure response parameters for sand and shale ($P_K$, Figure 7) are treated separately while bulk and shear moduli within lithofacies are assumed to have the same value.

Previous pilot studies on synthetic models (Stephen et al., 2004a and 2004b) and history matching for different parameter types (Stephen et al., 2005) enabled the elimination of several parameters. Simultaneous inversion of the five most important parameters is carried out including: two multiplier groups around I2 (Figure 5), a single pilot point permeability multiplier at I3 (Figure 6) and also the pressure response variables of sand and shale (Figure 7).

Figure 8 shows the misfit decreasing against the model counter and the parameters converge towards the best answer. Predicted impedance differences for the best model (Figure 9) show a marked improvement over the starting model as pressures and the seismic pressure response are reduced. The pressure response, originally taken from core measurements (MacBeth, 2004), is increased for sand but decreased for shale by a larger degree (a separate pressure response has subsequently been reported by the operator for this field). This agrees with the separate pressure response interpreted in the observed data (Figures 2 and 3). We find that the production data matches the well data very well (Figure 10a) and when predicting over 25 years, the similarity between models remains (Figure 10b).

The production misfit is much smaller than the seismic misfit here and is therefore less useful. This is mainly because the base case model was matched to the production data by the operator using conventional methods and the model with updated net:gross matches with the same accuracy (Figure 10a). The injection misfit is non-zero for both models, however, as the permeability near well I3 was too low. The well reaches the pressure limit and injection rates are no longer matched. This problem is resolved during history matching even though we do not use the injection misfit.

Following the history matching, we analyze the posterior probability density to determine the probability distributions of the five parameters (Figure 11). The pressure response parameters for the dry bulk modulus have a narrow distribution while there is still some uncertainty about the fault transmissibilities and the permeability multiplier. We also
examine how parameters affect the models in prediction mode. Figure 12 shows the average saturation and pressure distribution at four years along with uncertainty expressed as a standard deviation for each cell. Most changes are pressure rather than saturation related due to the low spatial frequency of changes to the flow parameters. The weighting applied during the averaging process is important because it allows us to properly assess the impact of a range of models by down weighting highly unlikely models. The changes in permeabilities and fault transmissibilities allowed here do not affect the prediction significantly.

Discussion
Seismic history matching can only be performed with good data. In this study, the dataset clearly shows a seismic response but we did find that it could be quite noisy. Our analysis (Soldo, 2005) suggested that a more refined set of localized cross equalization algorithms, such as 3D warping techniques (see Rickett and Lumley, 1998; Hall et al., 2005) or Singular Value Decomposition for time-lapse seismic processing (Reid et al., 2005) could be applied in future in order to decrease the level of discrepancy and the non-desirable 4D signature due to spatial misalignments. The anomalies around P1 were present as a result of activity above the reservoir and there was no obvious way to remove these. With these errors in mind, we are now investigating the process of modelling with improved data to determine how much the data quality can affect the prediction result.

The uncertainty analysis of the parameters is extremely useful for improving the reservoir characterization. Parameters that are highly uncertain after history matching may be ignored as having very little effect or revisited later when new well conditions apply. Highly certain parameters may validate or invalidate the original model with confidence given the exhaustive analysis that we use. With conventional history matching, where a small number of models are generated, the one model found by the engineer that gives the best match may disagree with the original model. It is unlikely that the geological modelling process will be altered based on one model, however. The same can be said of the petro-elastic parameters. If the history matching disagrees strongly with the core data, further analysis may be required. Here we have shown that the core data can be used as a guide but over predicts the pressure response of the 4D signatures.

Analysis of predictions beyond current history is also important. Knowledge of the location of the water front is crucial for the optimization of well control and to identify unswept regions. Similar analysis of pressures can be made to control gas break out but also to help with the estimation of changes in the seismic signal to guide future surveys.

The above analyses depend strongly on proper quantification of the posterior probability of each model. This requires calibration of the model error. The simulation model is often generated at coarse scales such that the flow is affected by numerical dispersion and over-smoothing of the permeabilities (Christie, et al., 2005). Conversion of coarse scale models to predicted seismic incurs a further error because of assumptions about saturation distributions and their interaction with the fine scale porosity. Work has begun to calibrate the model error using fine scale simulations and we hope to use interpolation of the error to other models similar to work described by O’ Sullivan (2004).

The posterior probability is also affected by the cross scaling necessary to ensure that seismic properties represent the same volume. Some workers have downscaled saturations and pressures prior to application of the petro-elastic transform (Mezghani et al. 2004) though this may not improve matters. Alternatively, the observed data may be upscaled areally which might require alternative error modelling.

Figure 8 Change in (a) misfit, (b) fault multiplier, and (c) permeability multiplier and (d) $P_K$ (see Figure 7) when all are varied simultaneously. The symbols are coloured to indicate the probability weighting relative to the most likely model. 128 models were created initially and many had a misfit above the maximum range on the graph. 64 new models were created each iteration in the vicinity of the best 32 ($ns = 64$, $nr = 32$).

Figure 9 Predicted impedance change for the best model obtained from history matching (a) 93-99 and (b) 99-00. The data has been normalized as in Figure 2.
Overall, we find that we must match the baseline survey to improve our chances of matching 4D seismic. In general it may be advantageous to modify the static model within the history matching loop. The approach taken here was more pragmatic where we were separated from the original geological modelling process and could only update the simulation model. A fully integrated approach is being investigated.

We have improved the reservoir description of the Schiehallion UKCS field by improving the match to seismic. Much of the improvement is found close to the injectors while around the producers, properties were already well determined from the operator’s original history matching of the model.

**Conclusions**

A multi-model approach to history matching has been developed to include seismic data systematically. In application to the Schiehallion UKCS field, we found that:

- Base line seismic (RMS amplitudes) should be matched prior to history matching.
- Reservoir description parameters such as fault transmissibility multipliers and petro-elastic transform parameters are all important, and simultaneous matching is necessary.
- Shale appears to have a different pressure response from sand, which is evident in the original data and from the history matching
- Saturations and pressures are predicted with low uncertainty for the parameters varied here giving confidence to future reservoir management including identification of unswept regions.

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**References**


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