Improved normalization of time-lapse seismic data using repeatability measures to improve automatic production and seismic history matching in the Nelson field.

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Abstract

Updating of reservoir models by history matching of 4D seismic data along with production data gives us better understanding of changes to the reservoir, reduces risk in forecasting and leads to better management decisions. This process of seismic history matching requires an accurate representation of predicted and observed data so that they can be compared quantitatively when using automated inversion. Observed seismic data is often obtained as a relative measure of the reservoir state or its change, however. The data, usually attribute maps, need to be calibrated to be compared to predictions. In this paper we describe an alternative approach where we normalize the data by scaling to the model data in regions where predictions are good. To remove measurements of high uncertainty and make normalization more effective, we use a measure of repeatability of the monitor surveys to filter the observed time-lapse data.

We apply this approach to the Nelson field. We normalize the 4D signature based on deriving a least squares regression equation between the observed and synthetic data which consist of attributes representing measured acoustic impedances and predictions from the model. Two regression equations are derived as part of the analysis. For one, the whole 4D signature map of the reservoir is used while in the second, 4D seismic data is used from the vicinity of wells with a good production match. The repeatability of time-lapse seismic data is assessed using the normalized root mean square (NRMS) of measurements outside of the reservoir. Where NRMS is high, observations and predictions are ignored. Net/gross and permeability are modified to improve the match.

The best results are obtained by using the NRMS filtered maps of the 4D signature which better constrain normalization. The misfit of the first six years of history data is reduced by 55 per cent while the forecast of the following three years is reduced by 29 per cent. The well based normalization uses fewer data when repeatability is used as a filter and the result is poorer. The value of seismic data is demonstrated from production matching only where the history and forecast misfit reductions are 45% and 20% respectively while the seismic misfit increases by 5%. In the best case using seismic data, dropped by 6%. We conclude that normalization with repeatability based filtering is a useful approach in the absence of full calibration and makes seismic data more reliable.

1 Introduction

It is becoming common for time-lapse (4D) seismic surveys to be used through the production life of a reservoir in order to better monitor fluid displacement (Hatchel et al. 2002; Waggoner et al. 2002; Vasco et al. 2003; Lygren et al. 2003; Portella and Mezghani et al. 2004; Emerick 2005; Huang and Lin 2006; Staples et al. 2006; Emerick et al. 2007). On the other hand using assisted and automatic methods for history matching (Arenas et al. 2001; Gosselin et al. 2001; Aanonsen et al. 2003; Clifford et al. 2003; Wang et al. 2005; Dong and Oliver 2005; Stephen et al. 2006; Jin et al. 2009; Aanonsen et al. 2009; Kazemi and Stephen 2009; Kazemi et al 2010) help us to find a better representation of the reservoir geologically as well as improving predictions of fluid flow behaviour. These approaches are less labour intensive per simulation run compared to manual approaches. The combination of automatic history matching techniques with 4D seismic data is even more complicated and is a continuing research topic.

Seismic history matching has been carried out using a number of approaches and it seems that each has its advantages and disadvantages. We use the stochastic neighbourhood algorithm (Sambridge 1999a) to update parameters once a misfit of seismic and production data has been generated (Stephen et al. 2006). The advantage of this approach is that misfit gradients do not need to be calculated as models are ranked by misfit and the parameter space is searched stochastically with iterative refinement. It also has the advantage over deterministic methods such as gradient based approaches (Gosselin et al. 2003) such that uncertainty analysis may be carried out and multiple solutions are obtained. On the other hand full simulations are required which is not the case for the ensemble Kalman Filter (EnKF). The latter is very successful in history matching to production data and it has been applied to include 4D seismic (Skjervheim et al 2007). However, the resulting size of the covariance and Kalman gain matrices are large and difficult to invert and require localization methods which does make that approach more difficult (Aanonsen et al. 2009).

Observed 4D seismic signatures obtained from attributes of the full stack data that represent the seismic properties of the reservoir and they are intrinsically a relative measure of change in the reservoir. They are derived from seismic amplitudes to represent acoustic or shear impedance but are not available as an absolute measure because the amplitudes themselves are
recorded in arbitrary units. For comparison to predicted acoustic impedance, they should be suitably calibrated to well data or normalized (or otherwise standardized). This is because history matching is an inversion process based on minimizing an objective function constructed from differences between observed and predicted data (just like model based seismic inversion). We therefore require that predictions and observations are made in the same units. Calibration of 3D and 4D seismic attributes to sonic- and density-log derived acoustic impedance can be made at the wells. As an alternative, we previously considered various approaches of normalization of observed data (Kazemi et al. 2010). We investigated the possibilities of using the whole dataset or, alternatively, focusing on seismic observations around vertical wells that gave good predictions of water cut. We found that in the latter case, we could calculate an optimal rescaling function, which lead to better history matched models as well as improvements in forecasts.

The field wide data used in the previous study was susceptible to uncertainty in the form of non-repeatability errors. In this study we measured repeatability using Normalized Root Mean Square (NRMS) of the seismic signals in regions of the dataset where no changes occur. Regions with high NRMS were then filtered from the observed 4D signature maps. We then performed normalization as before and repeated the automatic history matching to production and the 4D seismic signature to update the model. We also compared our results with the case where we only use production data in history matching. We evaluated the updated reservoir by forecasting the well production for three years for which we have historical production data and an additional seismic survey.

2 Automatic Production and Seismic History Matching loop

We perform history matching based on an automatic workflow presented in Fig. 1. We start with a base model supplied by the operator of the field which we perturb to generate new models. Prior to applying the automated step we analyse the behaviour of the base case model. We combine qualitative analysis of the predicted and observed 4D signature with analysis of the flow behaviour using streamlines (Kazemi and Stephen, 2010). This helps to determine where we should make changes to the reservoir. Localized changes to the model are controlled using pilot points with kriging (De Marsily et al. 1984). In this approach, modifications (i.e. multiplications) are made at the location of the pilot points and Kriging is used to interpolate those changes laterally. The changes are made uniformly through vertically stacked columns of cells within the reservoir interval (in Nelson there are three such intervals). Since we multiply the original properties, we avoid smoothing the reservoir and changes are made to the simulation scale model.

The automatic loop begins by first generating a number of new models via random sampling of the parameters that we seek to change as part of history matching. In each new model, a multiplier value is set for each variable at each pilot point and changes are propagated via Kriging. The models are then forward simulated with these changes to generate predictions of well behaviour as well as 4D seismic signatures, which in this case consist of changes of acoustic impedance. Predicted acoustic impedances for each cell are faster to compute than full time traces and we avoid issues of time shift and inversion in the modelling step. Observed relative acoustic impedance can be estimated from observed post-stack migrated seismic data by full model based inversion. Alternatively, pseudo-acoustic impedance may be obtained using coloured inversion (Lancaster and Whitcombe 2000). This process models sparse spike inversion as a convolutional process using an operator with an amplitude spectrum that converts the mean seismic spectrum to the acoustic impedance spectrum observed from logs. It also includes a 90 degree phase rotation to better represent the seismic response of layers rather than interfaces. As an approximation we only use the phase rotation following advice from the operator. It should be noted that coloured inversion provides a band limited relative impedance product. Full band-pass acoustic impedance may be obtained by kriging measured impedance profiles collocated by seismic stacking velocities (Kemper 2010). This may be used generate a low frequency model of acoustic impedance that is missing from the data that we use.

Predictions of acoustic impedances (for details see Stephen et al. 2006 and Stephen et al. 2009) are made by first calculating the bulk density along with the saturated bulk and shear moduli for each simulation cell using output from the simulator and a petro-elastic model. The bulk density is then

\[ \rho = \rho_{sa} \text{NTG}(1 - \phi) + \rho_{sh}(1 - \text{NTG}) + \phi(\rho_w S_w + \rho_o (1 - S_w))\text{NTG} \]  

(1)

where \( \rho_{sa}, \rho_{sh}, \rho_w, \rho_o \) are the densities of sand matrix, shale matrix, water and oil respectively, NTG is the Net:Gross ratio, \( \phi \) is the sand porosity and \( S_w \) is the water saturation. In the field studied here, laboratory measurements found that dry and shear bulk moduli follow quadratic equations in terms of porosity. The dry bulk modulus for each cell is then:

\[ \kappa_d = 32(1 - 2.07\phi + 2.38\phi^2) \]  

(2)

and the shear modulus is:

\[ \mu = 30.2(1 - 4.67\phi + 7.16\phi^2) \]  

(3)

The saturated bulk modulus was calculated using the Gassmann equation:
\[ \kappa_{sat} = \frac{\left(1 - \frac{\kappa_d}{\kappa_m} \right)^2}{\frac{\phi}{\kappa_f} + 1 - \frac{\phi}{\kappa_f} - \frac{\kappa_d}{\kappa_m} - \frac{\kappa_d}{\kappa_m}} \]  

where \( \kappa_{sat} \) is the bulk modulus of the sand grains and taken to be 37 GPa (Simmons and Wang 1971) and \( \kappa_f \) is the fluid modulus from:

\[ \frac{1}{\kappa_f} = \frac{1}{\kappa_o} + \frac{1}{\kappa_w} \]  

where \( \kappa_o \) and \( \kappa_w \) are the oil and water moduli respectively. These are pressure dependent with:

\[ \kappa_o = 10.15P + 2.44 \quad \text{and} \quad \kappa_w = 10.15P + 0.306 \]  

where \( P \) is pressure in GPa.

These equations are used along with grid cell pressures and porosity values to compute the dry bulk and shear moduli for each cell. From this the p-wave modulus is calculated and up-scaled vertically using Backus (1962) to give a single value for each cell over the reservoir interval:

\[ I_{mod} = \sqrt{\frac{\rho_k}{\kappa_k}} \left[ 1 + \frac{4\mu_k}{3\kappa_k} \right] \]  

where “\( <\kappa_\text{mod} \)” is the arithmetic mean over the depth weighted by cell volume. Each cell is divided into sand and shale and the appropriate shear and bulk moduli are used. Shale is dry and of constant bulk and shear modulus at 20 GPa and 6 GPa respectively. The average is then weighted by rock type volume. This is directly equivalent to applying a harmonic average within the cell and then averaging over the depth. Bulk density is similarly calculated. Seismic attributes are obtained as an equivalent pseudo- acoustic impedance property for each bin in the seismic cube. These data are then averaged using the volume weighted mean over each simulator cell to give a value that can be compared to the predicted data using

\[ I_{obs} = \langle I_{obs} \rangle_{ij} \]  

Where “\( <\rangle \)” is the volume weighted arithmetic average over the area of each simulator grid cell. The seismic misfit is then:

\[ M = \sum_U \frac{(\Delta I_{obs} - \Delta I_{mod})^2}{\sigma_d^2} \]  

The denominator, \( \sigma_d \), is a measure of the data and model errors which have been estimated to be uncorrelated and are obtained from the standard deviation of the time lapse signature in the region outside of the oil flowing region where the signal should be zero. A similar misfit is used for production data summing over time series data of oil and water production rates. The production and seismic misfits are added to give a total misfit.

The loop is closed using the Neighbourhood Algorithm (Sambridge, 1999a). In this process, models are first ranked in order of best misfit to identify the best \( n \) models. The parameter space (a multidimensional hypercube representing the multipliers used at the pilot points) is divided into voronoi cells to identify neighbourhoods of the models. Then \( n \) new models are generated by randomly selecting \( n_n \) (typically this ratio is 2) models from the neighbourhoods of each of the best \( n \) models. Another iteration is then repeated and so on until the user decides that convergence has taken place.

### 3 Normalization of time-lapse seismic signatures

Fig. 1 shows the history matching workflow. The stage where the observed seismic data is compared with predicted data, via Eq. 9, is indicated by the red box. We choose to compare attributes of acoustic impedance derived from measured amplitudes to predicted acoustic impedance. There are some challenges here, however. Migrated post-stack seismic amplitudes are invariably obtained in arbitrary units. They also depend on reflectivities at layer boundaries in a reservoir whereas we want to measure the layer properties themselves. Maps of pseudo-acoustic impedance for layers were obtained by first transforming the amplitudes using a ninety degree phase rotation operator. This is similar to coloured inversion (Lancaster and Whitcombe, 2000) where the two-way time traces are transformed into the frequency domain via fourier transform and then each frequency receives a ninety degree phase shift and the result is back transformed to two-way time. The root mean square of the data over the reservoir interval was calculated and this was found to be a good proxy for acoustic impedance by the operator. Approaches that produce relative impedance such as phase rotation and coloured inversion avoid the calculation of a low frequency model which may be needed because observed seismic data is missing low frequency data that should be present in acoustic impedance. As a result, the relative-acoustic impedance attribute is similarly in arbitrary units. In such a form the observed data (Fig. 2a) cannot be compared to the predictions (Fig. 2b) directly via Eq. 9. The derived observed map of
change in pseudo-acoustic impedances has a range from zero to several thousand in unspecified units. Fig. 2c, shows as an example, the synthetic and real 4D seismic signature of a cross line in the reservoir, further indicating the problem.

One approach might be to use well ties to help calibrate the observed data. Reflectivities may be derived from log-based acoustic impedance so that the wavelet can be deduced by inversion. This process is an iterative inversion step which begins with a first guess of the wavelet. The time trace of the seismic amplitude may be generated using one dimensional convolution. The wavelet is then modified and the time trace regenerated until a good match to the observed full stack, near-well, time trace is found. This approach requires good quality well logs along with precision in the depth to time conversion of the log data and t may be time-consuming. Similarly, it is very difficult to perform inversion of seismic data to saturation and pressure (as proposed by Landro, 2001 and with modifications by Trani et al, 2011) via deconvolution of the wavelet with observed amplitudes. Comparisons of forward modelled amplitudes to observed data is an alternative to comparing predicted and observed acoustic impedance as is comparison of inverted pressures and saturations to the model data.

As an alternative, normalization may be used to convert observed data to the appropriate dimensions. Fig. 2 schematises how the observed data can be normalized. We consider that predicted changes in acoustic impedance from a simulation case may be used to derive a transformation equation. There is a similar trend for the data, particularly indicating the 4D seismic active regions. The aim of this normalization study, then, is to convert the measured units of observed data (Fig. 2c, red line) to the same units of synthetic data (blue line), which ranges from zero to 0.3 km/s g/cc. We assume that there is a degree of correlation between the synthetic and observed 4D seismic data that is approximately linear and so we derive such an equation using least squares regression. We note that it is arbitrary whether we rescale observed or predicted data. We ultimately use Eq. 9 and this also contains a data error term, $\sigma_d$, which will similarly be set in the appropriate scale.

Normalization requires that predicted and observed 4D seismic data is available mapping equivalent data volumetrically. Observed data are obtained for each reservoir interval, in Nelson there are three such intervals. These data are obtained on a finer horizontal scale than predicted data so that they are then averaged areally onto the simulation grid using a volume weighted arithmetic mean (Fig. 3a) to obtain an observed measurement corresponding to the depth averaged prediction (Fig. 3b) obtained from Eq. 7. In other work (Stephen et al. 2006; Stephen et al. 2009) the predicted data was interpolated to the scale of observations. The advantage of averaging is that it smooths out some of the noise in the data. It is possible that some of the finer scale signal is due to real variations in rock or fluid distributions. However, the resolution of the model prevents matching at that scale so no information is lost in reality. If we don’t smooth the observed data we must then account for the resolution error in the model.

Two methods were defined for normalizing the observed 4D seismic signature:

**Map derived:** Observed and synthetic 4D seismic signatures from maps are used. In this work we use the whole map but alternatives might include just using regions where the match is considered to be good, which might just include active regions of the reservoir and so on.

**Well derived:** Predictions from selected simulation cells that contain well completions are compared. The focus here is on those wells with a good history match, in this case water cut, and also completed vertically so that only one column of cells is used.

Nelson has been produced by maintaining pressures above the bubble point and provided that the model does the same then a good water cut match indicates a good oil and water rate match as well. We may deduce that we have a good prediction of saturation near the wells. For vertical wells the average vertical saturation should therefore be reasonably accurate if the water cut is. For sub-horizontal wells this may not be the case, however, because a single water cut value representing the near well saturation could be obtained from a number of different saturation distributions and solutions may be non-unique. In addition, the porosity and net:gross were also considered to be accurately represented in the model at the well locations. This was quite reasonable given that the model was conditioned to the log data.

There is a choice of models that can be used for normalization. The most obvious is the base case. Alternatively, a model updated via Production History Matching (PHM) could be used. In this study the best PHM model was obtained via the method in our previous paper (Kazemi et al 2010), essentially performing PSHM without the 4D seismic misfit. It is not clear, a priori, whether the Map derived approach is better than the well equivalent, nor is it clear whether the base case or the production matched model should be used. The following sections discuss the approaches and the positives and negatives are summarised in Kazemi et al. (2010).

### 3.1 Non-repeatability measure

Marine seismic using towed streamers is susceptible to repeatability issues. Different surveys will experience environmental changes in water temperatures, salinity, tides and so on and variations in source and receiver locations can be important. The effect of variations between acquisition is measured using a repeatability quotient. Volumes of the dataset are identified where no seismic variation is expected and differences between seismic signal are analysed. The most common measure of repeatability is based on calculating the Normalized Root Mean Square (NRMS) between two seismic traces at two different dates.

For two traces, $a_t$ and $b_t$, within a given window $t_1 - t_2$, the RMS of differences divided by the average RMS of the traces is expressed as:

$$NRMS = \frac{200 RMS(a_t - b_t)}{RMS(a_t) + RMS(b_t)}$$

(10)
Where the RMS operator is:

\[ RMS(x_i) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \]

and \( N \) is the number of samples in the interval \( t_1 - t_2 \). NRMS ranges from 0 to 200 and is expressed with units of per cent.

4 Application

4.1 Nelson field

The Nelson field is an undersaturated oil field located in blocks 22/11, 22/6a and 22/12a in the UK Central North Sea. The first exploration well was drilled in 1967. 3D seismic data first acquired in 1985 and led to discovery in 1988. The first production began in 1994 and 27 production wells were drilled up to 2000. The original oil in place was estimated at 126 million cubic metres and up to end of 2000, 46 million cubic metres had been produced from the field (UK DTI, 2009). The production drive is aquifer supported coupled with water injection from 4 injection wells at the edge of the reservoir.

The reservoir sands in Nelson are turbidities with excellent reservoir quality with average net:gross of 70%, average porosity of 23% and permeability ranging from 200 to 1700 millidarcies. Geologically there are three distinct units in Nelson separated mainly by shale. Each unit has a channelized characterization. Sand beds are mainly confined channels. There is a varying degree of amalgamation of intervening shale deposits. The amount of shale and its distribution within and between the channels form the main uncertainty (Gill et al. 2012). Increased amalgamation reduces the volume and increases vertical permeability. On the other hand, shale drapes at the edges of channels act to reduce horizontal permeability. Therefore horizontal and vertical permeability as well as net:gross were modified to improve the history match. The combination of amalgamation and shale draping will define shale amount and distribution and control water movement in the reservoir (for details see Kazemi 2011).

3D seismic monitor surveys of Nelson have been carried out on a three year basis since production began. The monitor surveys were dedicated to 4D seismic acquisition (Boyd-Gorst et al. 2001; McInally et al. 2003). With a baseline survey in 1990, we are able to derive 4D seismic attribute maps on the reservoir level. We use amplitude data which has been phase shifted by 90 degrees to improve the tie between seismic polarity and lithology. This will modify the seismic trace in such a way that a peak or trough in a zero phase trace is changed to a zero-crossing to produce a pseudo-acoustic impedance equivalent to coloured inversion (Lancaster and Whitcombe 2000). This 3D cube is then converted to attribute maps using root mean square (RMS) averages of the time trace calculated between the horizons of the reservoir intervals. The difference of these attributes is used as the seismic 4D map. The 4D signature was found to be saturation dominated and so elastic and s-wave impedance were of little additional value.

The 4D maps were analysed to estimate the data error for Eq. 9. We assumed that noise in the 4D map was additive and then identified the regions of the map with zero signal (i.e. outside of the reservoir region). The standard deviation of the 4D signature in that region was then calculated and used as the data error. This was performed on the raw data and later transformed for the normalized data.

We carried out history matching by perturbing the model that was generated by the operator of the field (referred to as the pre-2009 model in Gill et al. 2012). This was made using conventional methods at a scale much finer than the one used for history matching. Facies and petrophysical properties were distributed and conditioned to the available well data as well as 3D seismic. The model was the upscaled for simulation by the operator.

4.2 Repeatability analysis

For the Nelson field, we obtain the NRMS map of phase shifted amplitude 4D seismic data which is represented in Fig. 4. From this picture it can be seen that there is a band in the middle where the NRMS is quite high. In the literature some researchers allow 30% of non-repeatability whereas others are able to reduce the figure to 15% (Craft et al. 2009). There remains a question of which value exactly should be the best threshold that can be considered for the NRMS map. For the Nelson field a 30% limit was chosen for this threshold to guide the calibration of observed 4D seismic and ultimately the time-lapse history matching. Using this threshold value, 10% of data over the Nelson map was removed.

Four regression equations were derived for normalization of the 4D seismic signature map. In order to distinguish easily between the four cases that we considered, suitable names were chosen (Table 1) which we will use in the rest of the paper. Fig. 5 shows the observed versus predicted 4D seismic data for the four cases in Table 1. The straight lines show the regression equations that were obtained by least squares minimization.

The regression equations varied depending on which data were used. Notably, the intercepts were relatively consistent at around 600 (of the arbitrary units) which was close to the average value of the portion of the data considered to contain no signal, as used to estimate the data error. The gradients of the equations contained the main differences. The map based gradients were almost half that of the well based gradients, roughly consistent with the previous study (Kazemi et al. 2010).
Clearly the map based cases contained data from regions where the model incorrectly predicted either strong or no 4D signature. A bias of one of these over the other will dictate the accuracy of the gradient. Filtering using NRMS removed data where the observed signal was low but the model incorrectly predicted strong signatures. Also, the NRMS filter was applied to the finer scale acquisition grid. It appears that high NRMS coincided with low values of observed 4D signature in simulation cells that otherwise contained larger values. When the filtered data was averaged (as in Fig. 3a and Eq. 8), the new 4D signature value was increased. These effects resulted in a larger gradient in the regression equation. Production history matching increased the saturations in some cells where the observed signal appears to be low or negligible. This made the gradient smaller.

The map based regression equations have considerably higher gradients compared to the well based case. NRMS filtering has also increased these gradients. After filtering out the cells with high NRMS, six out of the previous eight wells were available for use in the cross plot representing vertical wells with a good match, as shown in Fig. 5c. The cross-plot was more sparse, therefore. After production history matching, another well became unusable because it was not included in the history matching misfit and its prediction match deteriorated.

We obtained the normalized maps as shown in Fig. 6. Also shown are the sum of squares of difference between the normalized observed data and the base case model calculated over the data remaining after filtering using NRMS. A new data error estimate was calculated for Eq. 9 by scaling the standard deviation of the raw data for the non-signal regions of the map. Then, for each normalized map we calculated a separate error estimate.

In terms of production activity from the base model, 12 out of 27 wells over-predicted total water production and 15 under-predicted. The exact quantitative relationship between production and seismic activity is complex and depends on a lot of factors and is out of the scope of this paper. We could consider analyzing the wells that under predict and over predict and determine whether or not the normalized prediction follows a similar trend. However, underprediction of the seismic behaviour will only occur in the direct vicinity of the underpredicting well. Since the model is wrong, the true water sweep should either reflect water swept elsewhere or there should be a local material balance error resulting in significant drawdown. Unfortunately, selecting regions of under prediction near the wells is difficult.

### 4.3 History Matching set up

In this study we have targeted the 13 worst matching wells. At each well, between nine and twenty-five pilot points were used and all were changed by the same degree. The targeted wells make up 84 per cent of the total production misfit in the base case model. Seven of these wells are completed in the top geological interval so we do not change properties at those locations in the intervals beneath. In this case each history matching problem is three dimensional. The other six remaining wells that we focussed on are completed in both oil filled intervals where we updated properties separately. The problem is therefore six dimensional for these regions. Overall, the history matching contains 57 parameters. A summary of information is presented in Table 2.

The results in this paper are compared with our two previous history matching studies. In one of those studies we only used production data during history matching of Nelson. We relate current results to the best outcome from that study and call it the “PHM” case. More recently in Kazemi et al (2010) we considered normalization of the 4D seismic signature in history matching. In that case the best result we got was for Well+Base case which is very similar to the Well+base+NRMS.

### 4.4 History matching result

The four normalized 4D signature maps were used within the PSHM loop through identical history matching studies. We found that the production and seismic misfits were reduced by different degrees giving some improvement of the reservoir model for all four maps. However, the aim here was to find out which normalized 4D seismic signature would provide a better constraint of the reservoir in history matching. Examples of misfit convergence are shown in Fig. 7 plotted for selected wells from 3 different regions of the reservoir. Each well production misfit was minimised one at a time using the local multi-variable approach discussed in Kazemi et al. (2009). The seismic misfit was obtained for the whole reservoir albeit affected only by the region close to the specific well in each case.

After each individual well was history matched and the best pilot point properties obtained locally in each case the model was updated field-wide to incorporate the modifications. We assumed that the best model overall would consist of the best of each of the individual modifications (i.e. those that provided the lowest misfit locally), the second best model consisted of the set of second best local modifications and so on, and label those models as such. We verified that these assumptions were relatively accurate (Kazemi 2011).

The reduction of the misfits for the best overall model was compared in Fig. 8. From the reduction of field production misfit (Fig. 8a) it can be seen that regardless of the choice of method of normalization, the misfit was significantly reduced for all production wells. Well+best+NRMS shows the smallest reduction of the misfit compared to the others which was probably due to the fact that the seismic data error was smallest after it was modified along with normalization. The seismic misfit was dominant and it was harder to find models that satisfied both seismic and production data.

For the 4D seismic misfit reduction (Fig. 8b), there was a variable degree of improvement to the predicted 4D signature. The best occurred with the least improvement in production misfit. Also, the two Map derived cases saw the poorest improvement. The relative reduction of the 4D seismic misfit was somewhat less than for the production data. This was because the change in 4D signature was quite localized and much of the 4D seismic misfit actually came from noise in the non-reservoir region (around 50 per cent). The production misfit was of course very localized and it is relatively more affected by changes during PSHM.
The change in 4D seismic misfit is also calculated relative to the best PHM model and there was a reduction following PSHM. The best PHM model saw an increase in 4D seismic misfit in a number of regions and the value of seismic is demonstrated. The red bars show the combined reduction in misfit.

Fig. 9 shows the 4D signature prediction of the best history matched model for each normalization approach. Comparing each model with the base model (Fig. 6e) a general improvement of seismic in the middle of the reservoir was observed for all PSHM cases. For the PHM case, however, the 4D signature in the centre of the reservoir was increased, where we retained some of the incorrectly predicted 4D signature. The Map derived normalization cases, Fig. 9a and 9b, also resulted in a stronger predicted signature in certain regions to match the normalized observed data in Fig. 6a and 6b. We can summarise such that Map derived normalization enabled very good reduction of the total production misfit.

4.5 Updated reservoir model
The updated reservoir model was compared in each case with the best PHM and Well+base cases in Fig. 10 by plotting the multipliers used to change each reservoir variable during history matching. It is clear that the change at the pilot points was not consistent for all three variables. Some regions saw reduced net:gross but others saw an increase. The effect of increasing net:gross alone was to increase the 4D signature for a given saturation change. However, the increased pore volume slowed down the movement of the fluids, possibly reducing water saturation increase, particularly ahead of the front. There were several regions where the horizontal and vertical permeabilities were changed in the same direction (up or down) although the degree of change varies. The regions indicated by the arrows labelled “1” and “2” in Fig. 10 saw a different change between the PHM and PSHM cases. Horizontal permeability was reduced and vertical permeability was increased in the PHM case while in the PSHM case, the horizontal permeability increased and vertical permeability was increased or decreased. The net effect was that edge water drive was decreased for the PHM case and the opposite for the PSHM cases where edge water drive was generally increased elsewhere.

However, the selected regions 1 and 2 (Fig. 10) saw some 4D activity that was over predicted after history matching using production data only (PHM). The PSHM cases saw the false 4D signature removed by history matching. For Region 1, changes were made to improve the prediction of the wells by increasing vertical permeability such that the model had more bottom drive displacement. Seismic effects were then better captured also. In Region 2 for PHM all parameters were reduced while in PSHM cases horizontal permeability was increased.

Regions 3 and 4 in Fig. 10 contain two wells that under-predicted water production. It can be seen that in the Map+best+NRMS case, the fluid displacement was controlled in Region 3 by increasing horizontal permeability and decreasing vertical permeability. This increased the effect of edge drive towards the production wells. In Region 4, the water sweep was controlled by increasing net:gross and horizontal permeability. Compared to the Well+base+NRMS case in Region 4 the vertical permeability was decreased with no change to net:gross.

4.3 Forecast accuracy
We investigated the forecast ability of the best history matched models. We used production data from 2000 to 2003 and also the monitor from 2003. These data were not used in the history matching process.

Fig. 11 shows the cross plot of percentage reduction of forecast versus history production match misfits. Fig. 12 shows equivalent absolute production misfits calculated over the total simulation period (1994-2003), which includes the forecast interval, plotted versus the misfit the matching period (1994 to 2000). These plots indicate whether or not a well history matched model gives a good forecast. We found previously that without filtering by NRMS, the history match of equivalent “best” models was improved by 30-45% and the forecast was improved by up to 35%. The Well+base case performed best, albeit with a range of improved production forecast. When filtering by NRMS, the Well+best+NRMS failed to sufficiently improve the misfit and the forecast was worse. Well+base+NRMS performed somewhat as well as before although two of the ten best models had a worse forecast. The map derived models gave a consistently better improvement to the history match, by five percent at least, with less spread than before and also the models were more alike. On the other hand, there was a spread in forecast improvement but the best models matched those previously.

Fig. 13 shows a comparison of the oil and water production profiles for the best models of PHM and PSHM (Map+best+NRMS). The best PSHM case better matched the history of the wells and was better at forecasting than the PHM case. The two labelled wells (wells 1 and 2 in Fig. 13) are also shown even though they were not included as target wells for history matching. By integrating 4D seismic data, however, there was also improvement to those wells. This observation is additional evidence of the benefit of using 4D seismic in the history matching study.

5 Analysis

5.1 Does repeatability filtering help the history matching process?

The main aim of this study was to determine whether or not data from regions where repeatability was low might be degrading the normalization. The NRMS filter mostly affected the map-derived results (Fig. 11). It can be concluded that if the NRMS filter is not used, the best normalized 4D data will be generated based on the Well+base case leading to greater reduction of total production misfit. When the NRMS map was used to filter the cells with low repeatability, the resulting normalized observed map for the map derived cases provided even better reduction of total production misfit compared to the non-NRMS filtered cases.
Fig. 14 shows the best model multipliers for the Well+base and Map+best+NRMS cases after history matching. The degree of change was quite similar for some parameters in various regions. However for analysis, it is better to focus on specific regions. In Region 1 in Fig. 14, the ratio of horizontal to vertical permeability was increased for Map+base+NRMS case to increase the edge drive support. The same change was made for Well+base case but the $k_h/k_v$ ratio was not decreased in that case. In Region 2, for the Map+best+NRMS case, the water sweep was better predicted by increasing all parameters. However in the Well+base case, the vertical permeability decreased. Therefore, there is less effect of bottom drive displacement. The Map+best+NRMS case for Region 3 showed increased permeabilities whereas in Well+base there were also increased permeabilities but to a lesser degree.

5.2 Changes to the reservoir model after history matching

One important question to consider after history matching is how changes to parameters relate to changes to the modelled geology of the reservoir. In this section two updated reservoir models from previous studies were considered. These two models were better representative of the reservoir in terms of the reduction of the misfit values. Then the reservoir properties were compared with the base reservoir model as shown in Fig. 15.

In the Well+base case the net:gross value was increased up to 0.95 (northern part of Nelson field) which means a high proportion of sand was added to the reservoir. This change of net:gross was made in the Channel Axis. However, the horizontal permeability was also increased to a maximum 5000 mD in the north of Nelson field. On the other hand, in the Interchannel sands (centre of the reservoir), the reservoir became shalier because of reduction to the net:gross but the horizontal permeability is still high in some regions.

For the Map+best+NRMS case similar changes were made in the Channel Axis (North of Nelson) by increasing the net:gross and the horizontal permeability also increased. In the Interchannel there is low net:gross but the horizontal permeability was increased in this part of reservoir.

6 Discussion

In oil reservoirs that are produced with good pressure support such that the bubble point is not reached and when there is no gas cap, history matching inevitably tries to resolve errors in prediction of the water cut. The engineer will often deduce that errors in the base case model occur due to an incorrect volume of produced water either from horizontal or vertical flow. Understanding of the direction of flow is then important for selecting which flow properties to modify to improve the match. Too much channelling or fingering of flow or other physical dispersion will lead to earlier breakthrough being predicted with greater recovery of water. This will result if the horizontal permeability is too varied and history matching may homogenize the flow properties. On the other hand early breakthrough may arise through coning which is a vertical flow problem. The model may be changed by adding barriers or by reducing vertical permeability to reduce vertical flow. In the absence of 4D seismic data, the engineer is left with several viable options. The seismic data, however, lets the engineer know more clearly which direction the flow is moving and can reduce the options. The resulting models are more likely to be accurate.

Normalizing 4D seismic signatures is important for quantifying misfits in history matching. In many cases well tie information is not present for full calibration. Normalization relies on a model that is partly accurate, however. In this study a ‘blind’ approach using maps was compared to one where the wells were considered to match on saturation. The normalized maps contained a stronger 4D signature when the well data only was used. After normalization, regions of the predicted 4D signature map were found to contain significant errors which were removed by history matching.

The normalization process depends on the accuracy of the predicted acoustic impedances derived using the simulation model but also including the petro-elastic transform. We found that the choice of model did not matter. Uncertainties may arise in the prediction however, because of averaging issue when transforming from well logs to simulation cells. Secondly there is uncertainty in the equations used to calculate the synthetic seismic data because they were derived from lab studies and they may be unsuitable for the simulation scale or for in situ calculations (Menezes and Gosselin 2006; Kazemi and Modin 2010).

The choice of normalizing dataset was important for the resulting regression equation. In this work we assumed that the coefficients of that regression equation were well constrained. It is perhaps more correct to measure the uncertainty of those coefficients and include that in an updated data error for the seismic data. This then adds a more appropriate weight to the seismic misfit (via $\sigma$,$\text{Eq. 9}$) relative to production.

In this paper, the seismic data were normalized by using model data just once and the normalized data were fixed for the duration of history matching studies. It may be preferable to include the normalization parameters in the history matching loop. This approach could be considered in future work but it is possible that such an approach will result in increasing non-uniqueness and that there may be too many solutions that all fit with different regression equations. By tying the regression to the wells, a single regression equation seems more satisfactory and may be more stable in the inversion process. Alternatively, it may simply be a good starting point if the normalization parameters should be considered as changeable during history matching.

Even though 4D seismic data provides spatial information that production data is missing, in the constraint of simulation models, it has its own data uncertainty which has an impact on forecast uncertainty. In the context of this study, the normalized observed data will contain uncertainties from the relative measurements but also from the process used for normalization. The accuracy of the linear transformations are likely to add uncertainty and these depend on the petro-elastic model parameters, values of near-well porosity in the static model and also saturation distributions. Many stochastic methods of history matching may be applied to analyse the impact of uncertainty including gradual deformation, (Hu 2000), probabilistic perturbation
These approaches inevitably generate an ensemble of models that are found to match observations within data (and model) error and which can be analyzed. Distributions of both parameters and forecast results may be obtained to examine the reduction and remainder of uncertainty following history matching. Such approaches are recommended if uncertainty analysis is required. An advantage of the neighbourhood algorithm is that it generates a sizable ensemble of models during the inversion process. This enables an analysis of model parameters by computing the posterior probability density function of model parameters numerically via Bayes Theory. The misfit surface is sampled via NA to resemble the posterior probability density and then further sampled using a Markov Chain Monte Carlo method (Sambridge, 1999b). We can also extend this approach to analyse dependent variables in the model such as predicted acoustic impedance or flow properties such as saturation and pressure (Stephen and MacBeth, 2008) along with forecast data. This approach is more rigorous than some of the other stochastic methods but can be more costly to properly capture the probability distributions. An uncertainty study is recommended for future work in the context of seismic data normalization.

7 Conclusions
We make the following conclusions based on the work presented in this paper. Integrating appropriate time-lapse data with production data helped history matching of Nelson and resulted in a better forecast. Normalization suitably identified the zero change level in the observed data, NRMS also helped to better constrain the gradient of the map derived normalization equation. Map based normalization with NRMS led to improved history matching though some reduction of the forecast accuracy was seen. Using production data alone for history matching fails to capture the fluid movement properly far from the wells so the matched model predicts some unwanted 4D signature in the reservoir. Normalization is therefore a useful and necessary approach in the absence of better calibrated 4D seismic signatures.

Acknowledgment
We would like to thank the Nelson Field partners (Esso Exploration and Production UK Ltd., Idemitsu E&P UK Ltd., Premier Oil ONS Ltd., Shell UK Ltd., and Total E&P UK Ltd.) for providing the data and permission to publish the results. BP, Conocophiles, Shell and StatoilHydro are thanked for funding of this work: We thank Schlumberger Geoquest for use of their software. Malcolm Sambridge is thanked for use of the Neighbourhood Algorithm.

Nomenclature

\( a_t \) = the seismic trace for a given window, \( t_1-t_2 \)
\( b_t \) = the seismic trace for a given window, \( t_1-t_2 \)
\( n_i \) = the initial sample size for NA
\( n_m \) = total number of models generated by NA per iteration
\( p_{\text{mod}} \) = predicted acoustic impedance on the simulation grid, M/L²T, kgm²s⁻¹
\( p_{\text{obs}} \) = observed acoustic impedance on the simulation grid, M/L²T, kgm²s⁻¹
\( n_r \) = number of best models selected during NA
\( NTG \) = net:gross
\( P \) = pore pressure, M/L², Pa
\( RMS \) = root mean square
\( S_w \) = water saturation
\( t_{1-2} \) = two way time window, t, s
\( \Delta \) = time difference operator for 4D seismic calculations
\( \phi \) = porosity
\( \kappa_d \) = dry bulk modulus, M/L², Pa
\( \kappa_f \) = fluid modulus, M/L², Pa
\( \kappa_m \) = sand grain modulus, M/L², Pa
\( \kappa_w \) = fluid modulus, M/L², Pa
\( \mu \) = shear modulus, M/L², Pa
\( \rho_o \) = density of oil, M/L³, kgm⁻³
\( \rho_s \) = density of sand matrix, M/L³, kgm⁻³
\( \rho_b \) = density of shale matrix, M/L³, kgm⁻³
\( \rho_w \) = density of water, M/L³, kgm⁻³
\( \sigma^2 \) = data error

Superscripts

\( I,J,K \) = x,y and z indices on the simulator grid
\( i,j,k \) = x,y and z indices on the seismic grid
References


<table>
<thead>
<tr>
<th>Name</th>
<th>Seismic data</th>
<th>Model used for predictions</th>
</tr>
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<tbody>
<tr>
<td>Well+base+NRMS</td>
<td>Vertical wells</td>
<td>Base case</td>
</tr>
<tr>
<td>Well+best+NRMS</td>
<td>Vertical wells</td>
<td>Best after PHM</td>
</tr>
<tr>
<td>Map+base+NRMS</td>
<td>All of map</td>
<td>Base case</td>
</tr>
<tr>
<td>Map+best+NRMS</td>
<td>All of map</td>
<td>Best after PHM</td>
</tr>
</tbody>
</table>

Table 1 Names of the four normalization cases. NRMS was used to distinguish from equivalent cases investigated previously (Kazemi et al. 2010).

<table>
<thead>
<tr>
<th>Number of regions chosen for history matching</th>
<th>13 based on the streamline guide (Kazemi and Stephen, 2010)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reservoir variables updated</td>
<td>$K_{1s}$, $K_{2s}$ and $NTG$</td>
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<tr>
<td>Dimension per well</td>
<td>3D for 6 areas in first interval only</td>
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<tr>
<td></td>
<td>6D for 7 areas in both intervals</td>
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<tr>
<td>NA parameters</td>
<td>3D: $n_i=16$, $n_s=10$, $n_r=5$, total=66</td>
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<tr>
<td></td>
<td>6D: $n_i=128$, $n_s=18$, $n_r=9$, total=524</td>
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<tr>
<td>Production misfit</td>
<td>Oil and water rates for 13 wells</td>
</tr>
<tr>
<td>4D seismic signature</td>
<td>Derived from phase shifted amplitude</td>
</tr>
<tr>
<td>Parameterisation scheme</td>
<td>Local multi-variable (Kazemi and Stephen 2010)</td>
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<tr>
<td>Pilot point information</td>
<td>Pilot points separation: ~500m</td>
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<tr>
<td></td>
<td>Kriging variogram range: ~1500m</td>
</tr>
<tr>
<td></td>
<td>The number of pilot points per well: 9 - 25</td>
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</table>

Table 2 History matching parameters.
Figure 1: Schematic of the production and seismic history matching (PSHM) workflow (details in Stephen et al. 2006; Stephen et al. 2009), we focus on the red box in this paper for normalization of observed 4D seismic data.

Figure 2 Schematic of 4D seismic normalization. a) observed pseudo-acoustic impedance change before normalization, b) predicted change of acoustic impedance, c) comparison of observed versus predicted for the black cross line in the maps and d) observed 4D seismic signature after normalization.
Figure 3 Schematic of the location of a vertical well in a) seismic scale and b) reservoir scale. The red box in a) shows the boundary of seismic bins at the same location of the simulation cell in b. Arithmetic averaging was used to calculate one value of observed seismic for the red box and Backus (1962) averaging was used to get one value of synthetic seismic at the location of the well.

Figure 4 NRMS map calculated according to Equation 4 for the 2000-1990 time-lapse data and for the first reservoir interval. The black symbols indicate the wells in the field.
Figure 5 Cross-plots of changes in observed pseudo- and synthetic acoustic impedances for a) Map+base+NRMS, b) Map+best+NRMS, c) Well+base+NRMS and d) Well+best+NRMS. Error bars in c) and d) represent the standard deviation of the raw signature over each simulation cell.
Figure 6 Normalized observed 4D seismic signatures obtained by using the regression equation of a) Map+base+NRMS, b) Map+best+NRMS, c) Well+base+NRMS, d) Well+best+NRMS from Figure 7 and e) the synthetic seismic data for the base reservoir model. Black ellipses show the location of 15 production wells that under predict water rate for the base reservoir model. The figures are speckled because pixels have been filtered out where repeatability is limited and NRMS is high.
Figure 7: Misfit reduction for seismic and liquid production rate for each well for 3 different regions of the reservoir.
Figure 8 Reduction of misfits of (a) production and (b) 4D seismic signature for the best reservoir model from each history matching case. Reductions are compared to the base case model except for green bars which is a comparison to the best PHM model. The values in the blue box show seismic misfit of the base case model.
Figure 9 The best synthetic 4D signature after history matching for a) Map+base+NRMS, b) Map+best+NRMS, c) Well+base+NRMS, d) Well+base+NRMS and e) PHM model. The figures are speckled because pixels have been filtered out where repeatability is limited and NRMS is high.
Figure 10 Multipliers of properties changed in the base model via history matching for a) net:gross, b) horizontal permeability and c) vertical permeability in log scale. Note that actual changes to net:gross were limited so that unity was not exceeded and this is not reflected in the above plot. The black line indicates the initial Oil Water Contact.
Figure 11 Reduction of total production misfit for forecasting versus matching periods for different history matching studies. For each normalization case, the best ten models are shown.

Figure 12 Sum of misfits of the oil and water rates for all wells from 1994 to 2003 (history plus forecasting period) versus the same property but for 1994 to 2000 (history period only). Black star shows the base case misfit value.
Figure 13 Oil and water production rates in matched and forecast periods (light blue) for the best history matched model using production data only (gray) and using both production and seismic data (Map+best+NRMS) (light pink).

Figure 14 Best multipliers of the base model for two the best performing normalization processes from this study (Map+best+NRMS) and the previous Kazemi et al. (2010) study (Well+base) showing a) net:gross, b) horizontal permeability and c) vertical permeability in log scale.
Figure 15 Average reservoir properties in first reservoir interval for different history matching studies. (a) net:gross, (b) horizontal permeability and (c) vertical permeability.