Seismic assisted history matching using binary maps

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Abstract

This paper addresses the challenge of integrating 4D seismic data with production data in a quantitative manner in order to improve the forecasting ability of a reservoir model and reduce the associated uncertainty. It presents a history matching workflow that has been applied to production data and time lapse seismic data. In this procedure, the production data objective function is calculated by the conventional least squares misfit between the historical data and simulation predictions, while the seismic objective function uses the Current measurement metric between a binary image of saturation change. This approach is implemented on real field data from the United Kingdom Continental Shelf (UKCS), where uncertain reservoir parameters which consist of global and local parameters are initially assessed. These parameters include flow based multipliers (permeability, transmissibility), volume based multipliers (net-to-gross, pore volume), as well as the end points of the relative permeability curves (critical saturation points). After the initial screening, sensitive parameters are selected based on the sensitivity analysis. An initial ensemble of fluid flow simulation models is created where the full range of uncertain parameters are acknowledged using experimental design methods, and an evolutionary algorithm is used for optimization in the history matching process. It is found that the primary control parameters for the binary seismic gas match are the permeability and critical gas saturation, while the volumetric parameters are important for the binary seismic water match in this particular reservoir. This approach is compared to seismic history matching using full seismic modelling, preserving all amplitudes. The results demonstrate that the binary approach gives a good match to gas saturation distribution and water saturation distribution, and the reservoir parameters converge towards a solution. The conventional approach does not capture some signals of hardening and softening in the seismic data, hence in summary, the binary approach seems more suitable as a quick-look reservoir management tool. A unique feature of this study is the application of the binary approach using Current measurement metric for seismic data history matching analysis, as this circumvents the use of the uncertain petroelastic model. This approach is easy to implement, and also helps achieve an effective global history match.

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1. Introduction

Reservoir engineers desire the ability to predict the performance of an oil field in an efficient and timely manner; this is coveted as it expedites efficient reservoir monitoring, management, planning and economic evaluation (Obidegwu et al., 2014). In order to accomplish this objective, different procedures and mechanisms are employed to acquire, coordinate and interpret data obtained from the reservoir as input to the reservoir simulation model. This model has to confidently replicate the historical data for it to be considered worthy of realistic predictions, and this process of updating the reservoir model to satisfy the historical data is known as history matching. Over the past years, production data (oil rates, water rates, gas rates, pressure) have been the main historical data available, however, time-lapse (4D) seismic data is now considered a major dynamic input for history matching. That a model is matched to production data is not a sufficient condition for it to make improved predictions (Sahni and Horne, 2006), the model needs to integrate all available data as well as the geologists interpretation of the reservoir in order to provide the most representative reservoir model or models (Landa, 1997; Wang and Kovscek, 2002). The need to monitor fluid displacement is a great challenge that has been successfully overcome with the use of 4D seismic technology (Hatchell et al., 2002; Vasco et al., 2004; Portella and Emerick, 2005; Huang and Lin, 2006; Kazemi et al., 2011), which is the process of repeating 3D seismic surveys over...
a producing reservoir in time-lapse mode (Avansi and Schiozer, 2011). Quantitative use of 4D seismic data in history matching is an active research topic that has been explored extensively (Arenas et al., 2001; Aanonsen et al., 2003; Gosselin et al., 2003; MacBeth et al., 2004; Staples et al., 2005; Stephen and MacBeth, 2006; Kazemi et al., 2011; Jin et al., 2012), the main challenge being quantitatively incorporating the 4D seismic into the reservoir model (Landa, 1997; Walker et al., 2006).

Fig. 1 shows the different domains in which seismic data could be incorporated into the reservoir model as has been described previously (Stephen and MacBeth, 2006; Landa and Kumar, 2011; Alerini et al., 2014). The three main domains are: (1) The simulation model domain, where the observed seismic data is inverted to changes in pressure and saturation, and are then compared with the simulation output (Landrø, 2001); (2) The impedance domain, where the observed seismic data is inverted to changes in impedance, and the simulation model is forward modelled to derive impedances, and both impedances are then compared (Ayzenberg et al., 2013); or (3) The seismic domain, where the impedances derived from the simulation model are convolved with a wavelet to generate a synthetic seismic, and this is then compared with the observed seismic (Landa and Kumar, 2011). The aforementioned domains use seismic modelling, rock physics modelling or petrophysical modelling to address this challenge, however these modelling processes are complex, time consuming, use laboratory stress sensitivity coefficients, as well as Gassmann’s equation assumptions (Landrø, 2001; Gosselin et al., 2003; Stephen et al., 2005; Floricich, 2006; Amini, 2014). There have been other methods that circumvent the complex seismic modelling process (Landa and Horne, 1997; Kretz et al., 2004; Wen et al., 2006; Jin et al., 2012; Rukavishnikov and Kurelenkov, 2012; Le Ravalec et al., 2012; Tillier et al., 2013) which employed the use of image analysis tools, binary processing, or dynamic clusters to integrate the seismic data into the reservoir model. In this paper, a method is proposed where seismic data and simulation data are converted to binary seismic gas maps and binary simulation gas maps respectively, such that a comparison of the observed seismic data directly with the simulation output in the binary inversion domain is possible (Fig. 1). The objective function for calculating the misfit of the production data will be the popular least squares misfit, while the seismic objective function will be the Current measurement metric (Glaunès et al., 2008; Chassagne et al., 2016). This approach is contrasted with the conventional seismic modelling approximation scheme, and the context of the study is set by a UKCS field dataset.

2. Field data set

The binary seismic assisted history matching concepts in this paper will be applied to a real field data located at the United Kingdom Continental Shelf (Martin and Macdonald, 2010), with the aim of history matching the observed data, as well as forecasting the future production profiles and saturation distributions as a means of validating the new improved models. The main features of the data are that the reservoir pressure is close to its bubble point pressure, such that the commencement of production activities will lead to depressurization and gas exsolution; and that there is a subsequent pressure maintenance scheme in place by the use of water injector wells, so there will be water sweep distributions expected in the reservoir. The reservoir permeability is in the range of 200 mD to 2000 mD, with a reservoir porosity ranging from 25% to 30%. The pore compressibility is $7 \times 10^{-6}$ psi$^{-1}$, oil viscosity is 3.5 cp at reservoir temperature, water viscosity is 0.5 cp at reservoir temperature, and the oil formation volume factor is 1.16 rb/stb. Fig. 2 shows an outline of the reservoir, the position of the water injectors and oil producers, and the timeline of activity of the wells relative to the multiple seismic data surveys. There are 10 years of production activity from 1998 to 2008, and it should be noted that the history match will be implemented for the first 7 years, while the remaining 3 years will be used to validate the history matching process and forecasting ability. It should be also noted that the 3 years used for the forecasting analysis is not really forecast per se, but observed historical data which is held back to validate the history matching exercise. The simulation model was provided by the field operator, and its dynamic properties will be discussed in the next section.

3. Methodology

3.1. Simulation model conditioning

The simulation model used in this study has dimensions of approximately 9600 m by 4900 m by 700 m, and has 128 cells by 53 cells by 35 cells in the X, Y and Z direction respectively. The
simulation model runtime on a standard computer workstation (Intel CPU E5-1650 @ 3.20 GHz) with 6 processors is approximately 5 h. This computer specification will be used all through this analysis. In order to efficiently generate multiple runs of the model which is required in a history matching process, the runtime has to be reduced to an appreciable level; however this has to be achieved without distorting the output results, as the simulation model may give non-physical results if too coarse a grid is used (Carlson, 2003).

The initial model is modified and upscaled to different levels of coarseness shown in Table 1 and Fig. 3, and the output results are validated against the initial model output. The upsampling process involves rebuilding the grid structure to a coarser mesh, and using pore volume weighted averaging for the volumetric parameters, and flow based upscaling for the transmissibility parameters.

Table 1 shows the different models (model 1 to 7) that were created, their cell dimensions, their simulation runtime, and their least squares error misfits relative to the initial model. The total spatial misfit was calculated for pressure distribution, water saturation distribution and gas saturation distribution in the field, while the total well data misfit was calculated for oil production, gas production, water production and field pressure (Fig. 3 (a)). All these outputs were combined equally to generate the combined misfit. Fig. 3 (b) shows the total spatial misfit, total well data misfit and the combined misfit for the model outputs plotted against simulation model runtime.

Model 5 was selected as the most suitable model for the history matching exercise in terms of runtime efficiency and simulation accuracy. It was upscaled laterally by a factor of 4, such that its vertical heterogeneity is preserved and the material balance in the model is conserved so as to maintain the characteristics of the field geology and reservoir quality (King, 2007). Model 5 does not have the lowest misfit or the fastest runtime, but its selection makes the point that there is often a need to trade-off between simulation model output accuracy and simulation model runtime in every upscaling exercise as highlighted by Maschio and Schiozer (2003). They state that the loss of information is inevitable using any upscaling technique, and that the two key aspects that must be taken into account are the agreement of the results obtained from the upscaled model when compared to the initial model, and the upscaling computational performance. Having conditioned the simulation model to an acceptable runtime for history matching, the 4D seismic data is now conditioned to be an input into the history matching process.
3.2. 4D seismic data conditioning

The concept of 4D seismic data integration is to complement production data. 4D seismic data has broad spatial and low temporal frequency while production data has low spatial and broad temporal frequency (Jin et al., 2012). The corresponding characteristics of these data aid in obtaining realistic models of the reservoir through a seismic assisted history matching scheme. History matching is an inverse problem, it is a process of simultaneously perturbing reservoir parameters such that it can be represented as a minimization problem with the aim of reducing the misfit between the observed data and model predicted data through an objective function where observed dynamic data are used to condition the reservoir model. The use of the conventional least squares formulation for computing production data misfit has been shown to be suitable and efficient (Oliver and Chen, 2011), such that it can be significantly reduced during the history matching process, and properly characterizes the error between the simulated data and the real data. However, applying the least squares formulation to compute the seismic objective function and mismatch has been shown to be unsuitable because of the nature of seismic data (Aanonsen et al., 2003; Roggero et al., 2012; Le Ravalec et al., 2012; Tillier et al., 2013), hence the need to search for a suitable alternative.

Table 1

The parameters of the different upscaled models as compared to the initial model. Model 5 was selected as the most suitable model for the history matching exercise in terms of run time efficiency and simulation accuracy (see Fig. 3).

<table>
<thead>
<tr>
<th>Model</th>
<th>Cell Dimensions</th>
<th>Runtime (Mins)</th>
<th>Spatial Misfit</th>
<th>Well Data Misfit</th>
<th>Combined Misfit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base case</td>
<td>$128 \times 53 \times 35$</td>
<td>295.24</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Model 1</td>
<td>$32 \times 53 \times 07$</td>
<td>1.03</td>
<td>0.5066</td>
<td>0.5539</td>
<td>0.3073</td>
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<tr>
<td>Model 2</td>
<td>$64 \times 27 \times 17$</td>
<td>7.01</td>
<td>0.4372</td>
<td>0.6084</td>
<td>0.2978</td>
</tr>
<tr>
<td>Model 3</td>
<td>$32 \times 53 \times 35$</td>
<td>8.27</td>
<td>0.4942</td>
<td>0.6484</td>
<td>0.3268</td>
</tr>
<tr>
<td>Model 4</td>
<td>$128 \times 53 \times 07$</td>
<td>9.21</td>
<td>0.4150</td>
<td>0.6234</td>
<td>0.2942</td>
</tr>
<tr>
<td>Model 5</td>
<td>$64 \times 27 \times 35$</td>
<td>9.45</td>
<td>0.3919</td>
<td>0.5239</td>
<td>0.2616</td>
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<tr>
<td>Model 6</td>
<td>$64 \times 53 \times 35$</td>
<td>28.34</td>
<td>0.3597</td>
<td>0.4995</td>
<td>0.2448</td>
</tr>
<tr>
<td>Model 7</td>
<td>$128 \times 27 \times 35$</td>
<td>40.94</td>
<td>0.3953</td>
<td>0.5424</td>
<td>0.2674</td>
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</tbody>
</table>

Fig. 3. (a) shows the cumulative field oil production, cumulative field gas production, cumulative field water production and field average pressure for the initial base case model, the chosen model (model 5), and the worst case model after upscaling (b) shows the total spatial misfit, total well data misfit, and the combined misfit versus simulation runtime for all the upscaled models highlighting the chosen model 5 in a light green square. FOPR: Field Oil Production Rate, FGPT: Field Gas Production Rate, FWPT: Field Water Production Rate, FOPR; Field Production Rate. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
The proposed approach is such that the observed 4D seismic data is converted to binary seismic gas and water maps. The observed 4D seismic data is initially clustered and separated into ‘softening’ and ‘hardening’ signals; historical production data are then superimposed on the maps to aid the interpretation and deciphering of potential gas and water signals due to the injector/producer positioning, as well as the volumes produced which are represented by the size of the bubble in the bubble chart. Application of these processes leads to the final binary seismic gas and water maps as shown in Fig. 4. The softening and hardening signals on seismic are represented by red and blue colours respectively. The softening signal is as a consequence of pressure increase or gas saturation increase. A drainage process will give rise to a softening signal due to the different elastic properties of the fluids, as a non-wetting phase fluid displaces a wetting phase fluid, i.e. gas displacing oil or water, or oil displacing water. Conversely, a hardening signal is as a consequence of pressure decrease or an imbibition process, where a wetting phase fluid displaces a non-wetting phase fluid, i.e. water displacing oil or gas, or oil displacing gas. Fig. 4 highlights an example of generating the binary maps from 4D seismic data, by clustering the 4D seismic data into “hardening” and “softening” signals using k-means clustering, and then interpreting the binary gas and water signals with a validation against water injection and oil production at wells. The inter-mixing between water saturation, gas saturation and pressure signals in the 4D seismic data will likely be characterised in the “ambiguous signal” region (shown on the colour bar in Fig. 4), and will therefore not be captured by the binary approach.

For the seismic binary representation, a detectable change in saturation is assigned a value of one, while no change is assigned zero. The pore volume weighted gas and pore volume weighted water saturation difference maps (monitor year minus baseline year) are also generated from the simulation model and then converted to binary simulation gas and water maps, where a value of one also represents presence of gas or water respectively, and zero represents an absence of gas and water respectively. The binary seismic maps (gas and water) are then compared to those predicted from the simulation maps using a binary seismic objective function. The objective function is calculated on the simulation model scale, so the 4D seismic data is arithmetically upscaled to the simulation model scale before converting to binary maps.

In order to convert to binary maps, cut-off values representing thresholds need to be obtained. These can be derived from a calibration exercise using seismic forward modelling, or by interactive interpretation which requires a clear understanding of the 4D seismic response in terms of the dynamic behaviour of the reservoir (Jin et al., 2012). A combination of both methods is utilised, where seismic forward modelling is used to determine the initial threshold values in collaboration with k-means clustering; then integration of reservoir engineering knowledge, injector and producer well activities, reservoir geology and structural contour, as well as 4D seismic concepts are applied to generate the binary seismic maps.

The procedure for interpreting a suitable threshold is shown below:

a. To interpret as exsolved gas, the reservoir pressure should be below bubble point pressure, or at least should have previously been below bubble point pressure, so that there will be gas (exsolved gas) present in the reservoir.

b. The presence of gas signal around a producer well is validated from gas production profile of the well.

c. The gas may be present at expected locations, for example at local structural highs.

d. The presence of water is expected around water injector wells.

Fig. 4. The process of generating the binary (gas and water) maps from the 4D seismic data. The 4D seismic data are initially clustered and separated into ‘hardening’ and ‘softening’ signals; historical production data are then introduced to aid the interpretation and deciphering of potential gas and water signals due to the injector/producer positioning, as well as the volumes produced which are represented by the size of the bubble in the bubble chart. Application of these processes leads to the final seismic binary gas and water maps. Inset shows the 4D seismic colour bar in amplitudes and the associated physical interpretation of the 3 subset regions.
e. Being aware that amplitude decrease (softening) in the 4D seismic data is as a consequence of gas, as well as pressure increase (Calvert et al., 2014), the amplitude decrease caused by an increase in pressure around a water injection well is removed from the analysis; however in the case of a gas injector well (where an increase in pressure and the presence of gas cause the same softening effect on seismic data), the magnitude of the pressure and gas saturation will need to be determined in order to ascertain which has a more dominant effect on the seismic data. It should be noted that there are no gas injector wells in the data provided for this reservoir of interest.

f. The same as above applies to an amplitude increase (hardening) in the 4D seismic data, which can be as a consequence of water saturation or pressure decrease, as it is unlikely for injected water to coincide with a pressure decrease; hence any hardening signal that is not around an injector well is ignored.

3.3. Binary objective function

The Current measurement metric (Glaunès et al., 2008) is used as the binary seismic objective function to quantify the similarity/dissimilarity between the binary simulated pore-volume weighted saturation difference map and the binary 4D seismic data difference map. Some of the advantages of this binary approach are that it eliminates the magnitude of the difference in values of the simulator output and pressure decrease, as it is unlikely for injected water to coincide with a pressure decrease; hence any hardening signal that is not around an injector well is ignored.

petro-elastic model procedure, it provides a means of comparing the observed seismic data to the simulation model output, and that it is a fast and effective method of extracting useful information from the data. It should also be noted that the selection of appropriate weight coefficient values for obtaining the objective function is usually driven by reservoir engineering experience and can be case-dependent (Tillier et al., 2012). For the production data, the practice of boosting the effects of the ill-fitted production data is adopted, and this is done by selecting the weights as being proportional to the square of the difference between the data computed for the base case model and the observed data (Kretz et al., 2004); while the different time steps of the binary seismic data are equally weighted. The combined production data and 4D seismic data objective function is normalized (Kretz et al., 2004) such that at the initial iteration of the history match, the combined misfit is a value of one, and this is shown in equation (1) below:

\[ O.F. = \frac{1}{2} \sum_{i=1}^{N_p} (h_i - s_i)^2 + \frac{1}{2} [H_{CMM}] \]

where \( N_p \) represents the production data analysed, \( h \) is the historical observed data while \( s \) is the simulated output. The \( H_{CMM} \) is the current measurement metric (Glaunès et al., 2008) we have chosen to compare the misfit between the seismic and simulated binary images and it is represented by equation (2).

\[ H_{CMM} = \sum_{i,j=1}^{N_s} K_{ij} |\tilde{A}_{ij} - \tilde{B}_{ij}|^2 \]

where \( N_s \) represents the seismic time steps, \( A \) and \( B \) are the seismic...
and simulation binary maps respectively, $\vec{A}_i$ and $\vec{B}_j$ denote the $(i,j)$-th Fourier coefficients of $A$ and $B$, and $K$ is the smoothing kernel. The smoothing kernel is mathematically represented by equation (3):

$$K_{ij} = \left( i^2 + j^2 \right)^p \left( 1 + \sqrt{i^2 + j^2} \right)^p$$

where $p$ is the smoothing parameter. When $p$ is small the norm becomes more local, which means that small details are well measured but large translations are not captured; however as $p$ becomes large, the norm becomes large and small details are missed while the larger displacements are well measured. More details on the Current measurement metric and the smoothing kernel can be found in Chesseboeuf et al. (2015), applications and tests using this metric can be found in Chassagne et al., 2016.

3.4. Setting the scene

To perform the history match, an initial ensemble of models is created using the Latin Hypercube Experimental Design (LHED) method as implemented in Roggero et al. (2007), as multiple models have extensive coverage of the search space and deliver

![Fig. 6. The sensitivity analysis of the initial 104 parameters to the production data (oil, gas and water) of wells P1 and P2, and also to the binary gas and water maps. The most sensitivity parameters are shown (top seven). From these parameters, 35 are selected for the history matching exercise. Also shown are the initial geobodies, and the selected geobodies after the sensitivity analysis.](image)

Table 2

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Number</th>
<th>Lower Limit</th>
<th>Start Value</th>
<th>Upper Limit</th>
</tr>
</thead>
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<td>0.35</td>
<td>1</td>
<td>2</td>
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<td>Global Perm. Multiplier</td>
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<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Global Poro. Multiplier</td>
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<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Global Pore Vol. Multiplier</td>
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<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Transmissibility Multiplier</td>
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<td>1</td>
<td>3</td>
</tr>
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<td>Regional NTG Multiplier</td>
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<td>0.35</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Regional Perm. Multiplier</td>
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<td>0.35</td>
<td>1</td>
<td>5</td>
</tr>
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<td>Regional Pore Vol. Multiplier</td>
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<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Critical Water Saturation</td>
<td>1</td>
<td>0.4</td>
<td>0.428</td>
<td>0.5</td>
</tr>
<tr>
<td>Critical Gas Saturation</td>
<td>1</td>
<td>0</td>
<td>0.001</td>
<td>0.05</td>
</tr>
<tr>
<td>Total Number of Parameters</td>
<td>35</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
robust results. The initial input parameter sampling is important, and is usually carried out using experimental design methods, such as Plackett-Burman, LHED or Factorial Design (Schulze-Riegert and Ghedan, 2007; Zubarev, 2009). The LHED is a statistical method for generating a sample of plausible collections of parameter values from a multidimensional distribution, and it is useful for exploring the uncertainty range (Schulze-Riegert and Ghedan, 2007; Risso et al., 2011; Maschio and Schiozer, 2014). An optimization algorithm is required for the optimization process in order to calibrate uncertain values in the reservoir. The optimization algorithm should be robust with suitable performance, deliver reproducible results and solutions within the uncertainty framework, and be simple to understand and implement (Schulze-Riegert and Ghedan, 2007). The evolutionary algorithm satisfies these conditions, and covers a broad application area, and has been used extensively for reservoir history matching (Schulze-Riegert and Ghedan, 2007; Maschio et al., 2008; Aranha et al., 2015). It is a derivative-free optimization method, as it does not require the computation of the gradient in the optimization problem (which will require access to the simulator source code), and utilises only the objective

Fig. 7. Normalized production profiles for wells P1 (left column) and P2 (right column) highlighting the improved model responses (dark blue lines), after history matching to production data and binary seismic (gas and water), using Current measurement metric. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
function value to determine new search steps. The basic outline of the evolutionary algorithm is based on the notion of Darwinian evolution where natural selection inspires “survival of the fittest” which leads to an increase in population fitness. The selection of new search steps are generated by applying recombination and mutation operators which generate new set of outputs. Based on their fitness, some of the outputs from the previous generation are considered for the next generation, and this process continues until outputs with sufficient fitness are found (Schulze-Riegert and Ghedan, 2007).

In history matching, the termination criteria which signifies the completion of the exercise is usually until the objective function is small enough, convergence is obtained, or the number of iterations exceeds a maximum value (Tillier et al., 2012). The termination criteria used in this work is the convergence criteria. When convergence of the objective function is achieved, an improved set of models and their accompanying uncertainty is generated. The uncertainty is generated as a function of the variation in the response parameters. The probability redistribution of the a priori uncertain parameters reduces the spread of the a posteriori distribution, and as a direct consequence, reduces the dispersion of the reservoir response parameters, hence mitigating risk and uncertainty (Maschio and Schiozer, 2014). One of the advantages of using this approach is that multiple initial realizations can be updated to match the same dynamic data to assess uncertainty reduction in the reservoir characterisation due to the integration of dynamic data, and this is similar to the randomized maximum likelihood method (Liu et al., 2001; Wen et al., 2006).

As has been mentioned, the history matching exercise will be applied using production data alone, binary seismic data (gas and water independently) alone, and the combination of production data and binary seismic data (gas and water). Fig. 5 shows the workflow for the binary seismic assisted history matching which has been developed using Python programming language and MEPO software.

3.5. Model parameterization

In order to proceed in a history matching exercise, pertinent reservoir parameters have to be perturbed. Over the years of production in this reservoir, it has been observed that the major challenges to the field development and management plan are the field connectivity and the representation of its numerous geobodies. These geobodies were derived from the 3D seismic interpretation and used for geological model construction. An experimental design sensitivity study starting with 104 parameters was implemented to determine which parameters and geobodies were most significant to the seismic assisted history matching objective function.

Fig. 6 shows the top 7 most significant parameters of the sensitivity analysis for gas production, oil production and water production for wells P1 and P2 which would be used for the history matching study, as well as the binary gas and water maps. Combining the geobody regions and global parameters, 35 parameters were identified for the history matching exercise. These include the permeability multipliers, porosity multipliers, net-to-gross multipliers, pore volume multipliers, geobody

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**Fig. 8.** The seismic binary (gas and water) maps compared to the simulation binary (gas and water) maps highlighting areas of mismatch. The first 4 monitors (the first four rows), i.e. first 7 years will be used for the history matching exercise, while the last 2 monitors (the last 2 rows) i.e. last 3 years will be used for the forecasting analysis.
transmissibility multipliers, connate water saturation and critical gas saturation. Table 2 shows all the parameters and the ranges used. The starting values of the parameters are the initial values, while the ranges are selected generally based on engineering judgement to cover possibilities, and such that the perturbed model remains physically and geologically meaningful and consistent with the initial understanding of the field.

The upper limit of the volumetric parameter multipliers (NTG, porosity, pore volume) is twice their initial value, which explores most possibilities, while the lower limit is 0.35, such that the reservoir cells are not de-activated. The upper limit of the transmissibility multiplier is three times the initial value, while the lower limit is zero, thus preventing any flow or communication across the transmissible boundary. The upper limit of the permeability multiplier is 5, while the lower limit is 0.35. The upper limit of the critical water saturation, which is the saturation at which the water would gain mobility is 0.5, while the lower limit is 0.4. The upper limit of the critical gas saturation, which is the saturation at which the gas would gain mobility is 0.05, while the lower limit is 0, which implies that at the point of gas exsolution, the gas becomes mobile immediately. These range of values have been identified in order to characterize the reservoir in a realistic manner, however it is noted that the end values which are the limits might not be very practical, but are useful to use as limits.

4. Application of binary seismic history matching

The initial state of the reservoir, base case conditions and improved models of the history matching process are shown in Figs. 7–9. Fig. 7 shows the observed data, the base case model, the initial ensemble and the improved models of the response parameters (oil production rate, gas production rate and water production rate) of wells P1 and P2 which have been selected for this history matching exercise due to their location and availability of historical data. The observed data represents data measured at the wells, the base case represents the initial model’s production profile, while the initial ensemble represents profiles for the models generated using the Latin Hypercube Experimental Design which encompasses the effects of the defined uncertain parameters.

The observed oil production rate and gas production rate of producer well P1 drops continuously for the first 3 years until an improved oil recovery plan is put in place by introducing injector well I5 to provide pressure support as well as water to sweep the oil. This action stabilizes the production rate for the subsequent years. The same trend is observed for producer well P2, however the oil production rate drops continuously for the first 4 years until an inefficient injector well is replaced. The introduction of the new injector well boosts and maintains the oil production rate for the subsequent years until it gently declines.

The gas production rate of producer well P2 is high for the first 4 years as there is gas exsolution in the reservoir due to poor pressure maintenance, when this is curbed by introducing an injector well, the gas production rate drops and declines in the subsequent years. There is also uncertainty on some sporadic high values of gas production rate on producer well P2 which can potentially be attributed to noise errors (e.g. faulty gauge or just inaccurate readings). The water production in wells P1 and P2 occurs significantly in the later years due to a rise in water cut from the water

Fig. 9. The updated binary simulation maps compared to the binary seismic maps highlighting areas of improvement after history matching to production data and binary seismic (gas and water), using Current measurement metric.
Fig. 8 shows the comparison of the seismic binary gas maps versus the simulation binary gas maps, and the seismic binary water maps versus the simulation binary water maps. The gas maps show evidence of exsolved gas in the early years, and declining gas volumes in the later years; while the water maps show little amount of water in the early years but the water comes into full effect in the later years. The first 4 monitor surveys corresponding to the first 7 years will be used for the history match, while the last 2 monitor surveys corresponding to the remaining 3 years will be used to analyse the forecast. The areas of mismatch are highlighted with question marks on the simulation binary gas and water maps as compared to the seismic binary gas and water maps respectively, and getting the maps to match is the aim of the seismic assisted history matching exercise.

To history match to both production data and binary seismic data (gas and water), their combined objective function is weighted equally as previously stated, as per Kretz et al. (2004). After history matching to both production data and 4D binary seismic data, the updated production profile and saturation distribution are shown.
in Figs. 7 and 9. Fig. 7 shows the production profiles of the updated models (in dark blue colour) and there is an improvement, while Fig. 9 shows the updated simulation binary maps compared to the seismic binary maps highlighting areas of significant improvement on both the updated gas maps and updated water maps. Fig. 12a shows the histograms of selected converging parameters, where the horizontal permeability multiplier is about 2.0, the critical gas saturation value tends towards a value of 3.5%, and the pore volume multiplier is approximately 1.1.

The history matching exercise is also conducted when matching to production data alone, binary seismic gas data alone, and binary seismic water data alone (Obidegwu, 2015), and their forecast ability will be discussed.

5. Application of seismic modelling approximation

In order to implement a seismic assisted history matching scheme, the 4D seismic data has to be integrated into the history matching loop. A procedure previously proposed and used by MacBeth et al. (2004), Floricich (2006), Fursov (2015) and MacBeth et al. (2016a) which enables quantitative estimation of the similarity between the seismic data and the simulation model output will be adopted as the conventional method. A relationship between the seismic data and the average maps of the reservoir simulation output dynamic properties (pressure distribution, water saturation and gas saturation) is proposed and analysed. Co-efficients are derived which determine the impact of the individual dynamic properties on the generated seismic data, and a scalar map (ideally the baseline seismic) is applied to the dynamic properties so as to capture the effects of the reservoir geology, porosity, net-to-gross and general static properties. These relationships will be used to generate the seismic response, thus avoiding a full physics seismic modelling which is time consuming.

For the history match to both production data and seismic modelling, their combined objective function has weights of equal proportion as stated previously. After history matching to both production data and seismic modelling, the updated production profile and 4D seismic data proxy are shown in Figs. 10 and 11.
Fig. 10 shows the production profiles of the updated models (in dark blue colour), and there is an improvement. The third column on Fig. 11 shows the history matching to production data and 4D seismic data proxy maps compared to the observed 4D seismic maps (second column). There are some areas of hardening and softening signals match. Fig. 12b shows the histograms of selected converging parameters, where the horizontal permeability multiplier is about 2.5, the critical gas saturation value tends towards a value of 2.5%, and the pore volume multiplier is approximately 1.2. The history matching exercise is also conducted when matching to the 4D seismic data proxy alone (Obidegwu, 2015), and the forecast ability will be discussed.

6. Discussion

It has been shown that constraining the reservoir simulation model to a variety of data (4D seismic data, production data, both) affect the updated parameters differently, ideally more constraints mean a better history matching solution (Wang and Kovscek, 2002; Katterbauer et al., 2015). When matching to binary seismic gas, the permeability multipliers and critical gas saturation converged to a reasonable degree, while the volumetric parameters (porosity, net to gross) remained relatively unconstrained. However, when matching to binary seismic water, volumetric parameters appear to have a strong effect. Also the seismic modelling approximation analysis seemed to improve the seismic match but the parameters did not converge fully. In order to have a better grasp on this analysis, the objective function and uncertainty for the scenarios are plotted as shown in Fig. 12c. These have been normalized to a value of 100 and 1 respectively for ease of comparison. It is observed that combining the production data and binary seismic (gas and water) reduces the uncertainty and gives a reduced misfit value (Huang et al., 1998; Walker and Lane, 2007; Jin et al., 2011). The objective function and uncertainty of the proxy seismic...
analysis give relatively higher values, and a possible cause is that the absolute magnitude of the signals, as well as their positioning are being matched, hence making it more challenging. By comparing the updated models prediction with the initial model predictions (Tables 3, 4, 5 and 6), the forecasting ability can be assessed. It is found that matching to binary seismic gas alone gives a 26% improvement, matching to binary seismic water alone gives a 25% improvement, while matching to combined production data and binary seismic (gas and water) gives a combined 46% percent improvement, with 58% improvement on well data match. On the other hand, matching to proxy seismic alone gives a 31% improvement, while matching to combined production data and proxy seismic gives a combined 37% improvement, with 44% improvement on well data match. It is observed that combining the production data and binary seismic (gas and water) produces a more effective forecasting result than using the proxy seismic analysis. Matching of production data alone will produce models that match the reservoir behaviour at the wells, but these will not be consistent with the overall fluid-flow behaviour (Kretz et al., 2004), and this is why the introduction of 4D seismic data is necessary (Oliver and Chen, 2011; Katterbauer et al., 2015; Stephen and Kazemi, 2014; Tolstukhin et al., 2012), so as to capture the area in-between the wells and hence obtain a more robust predictive model. It can be concluded that for this case study, combining the production data and binary seismic (gas and water) produces the most effective result and it is believed that this method should be applicable to other case studies and produce similar positive results.

Overall, the seismic integration within the history matching procedure is still an open question. If the seismic domain approach (Landa and Kumar, 2011) is selected, seismic modelling and a petro-elastic model have to be designed, and this introduces a significant uncertainty into the model. If we decide to bring the seismic to the pressure/saturation domain, the petro-elastic modelling is still a necessity, as well as an inversion process which is non-unique (Jin et al., 2011; Landrø, 2001). Finally an intermediate domain can be used, the seismic impedance domain, this is the preferred approach in most literature (Gosselin et al., 2003; Reiso et al., 2005; Roggero et al., 2007; Emerick et al., 2007; Ayzenberg et al., 2013). Nevertheless this last option also exhibits the disadvantages of the previous ones. These different approaches require a lot of time to establish the appropriate rock physics model or seismic modelling, moreover the uncertainty within these methods are very significant, which does not help to establish a robust update of the model. Some attempts to circumvent these issues have been published (Landa and Horne, 1997; Kretz et al., 2004; Wen et al., 2006; Jin et al., 2012; Rukavishnikov and Kurelenkov, 2012; Le Ravalec et al., 2012; Tillier et al., 2013; MacBeth et al., 2016b) using image analysis tools, binary processing, dynamic clusters or a seismic proxy, they constructed a more or less direct relation between the seismic and the simulation domain. The comparison of the uncertainty on the updated model across methods is not an easy task and rarely achieved, especially when it is applied to a real dataset. In this study we applied to a UKCS field dataset, a 4D seismic history matching method, which circumvents the conventional seismic modelling approach. Also we compared the binary methodology to a seismic history matching exercise using a seismic proxy, the setting up of a conventional seismic history matching as show in Fig. 1 would have been an ultimate comparison but extremely costly in terms of computing time and choices for the whole workflow which is often a matter of debates. The quantification of uncertainty/errrors and strict comparison in between seismic history matching methods should be a preoccupation when it comes to test a new methodology, even if needed, it is really not a trivial assessment.

7. Conclusion and future work

Field scenarios that this method can be applicable to are fields that exhibit gas exsolution (Kretz et al., 2004), water flood patterns (Jin et al., 2012), and have identifiable seismic signals. This is required in order to implement the interpretation of the data as well as conversion to binary maps. For scenarios where there is uncertainty on the threshold values, a ternary (−1, 0, +1) representation of the signal might be suitable as this helps reduce the ambiguous region in the binary representation, also this additional information could serve as a quantification of the uncertainty in the binary seismic history matching process.

In addition for thick reservoirs (i.e. reservoirs above tuning thickness), a binary volumetric approach may be more suitable, as opposed to an averaged binary map method, but then the question of how to include the third dimension in the objective function has to be thought carefully.

Apart from the fact that this method is circumventing the traditional way, the binary mapping has the ability to characterize physical features we are sure of and use only this information to update the model which is by itself a certain philosophy on seismic history matching, instead of massive data integration, we carefully select what should be used to update the model.

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