Results of the First Norne Field Case on History Matching and Recovery Optimization Using Production and 4D Seismic Data

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This paper was prepared for presentation at the SPE Annual Technical Conference and Exhibition held in San Antonio, Texas, USA, 8-10 October 2012.

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Abstract

In preparation for the SPE Applied Technology Workshop, ¨Use of 4D seismic and production data for history matching and optimization – application to Norne (Norway)¨ held in Trondheim 14-16 June 2011, a unique test case (Norne E-segment) study based on real field data of a brown field offshore Norway was organized to evaluate and compare mathematical methods for history matching as well as methods on optimal production strategy and/or enhanced oil recovery.

The integrated data set provided an opportunity to discuss emerging and classical history matching and optimization methods after being tested using real field data. The participants of this comparative case study were expected to come up with a history matched model preferably using an integration of production and time-lapse seismic data and with an optimal production strategy for the remaining recoverable resources for the future period. Participants were allowed to suggest techniques to enhance recovery. Taking into account that the Norne benchmark case is a case study based on real data and no one exactly knows the true answer, participants and delegates were encouraged to discuss the methods, results and challenges during the course of the workshop, and thus in this case there are no winners or losers. Everyone who participated gained experience during the course of the exercise.

Participants were asked to history match the model until the end of 2004 and optimally predict the production (oil, water and gas rates) performance until the end of 2008. Participants were from different universities in collaboration with other research organizations namely Stanford University in collaboration with IBM and Chevron, TU Delft in collaboration with TNO, Texas A&M University, and NTNU in collaboration with Sintef. This paper summarizes the presented results from these groups and the outcome of the discussion of the workshop delegates.
Introduction
The Center of Integrated Operation in petroleum industry at NTNU (IO Center) in conjunction with the Society of Petroleum Engineers (SPE) organized an applied technology workshop about the use of real data from the Norne Field. The workshop attracted 80 delegates and international speakers from more than ten countries all over the world, namely the United States of America, Saudi Arabia, the Netherlands, Brazil, Denmark, Angola, Nigeria, the United Kingdom, Russia, India, and Norway.

The uniqueness of this workshop was that it addressed for the first time a comparative case study that uses real field data that includes time lapse seismic data. The purpose of reservoir management is to control operations to maximize both short- and long-term production. This consists of life-cycle optimization based on reservoir model uncertainties together with model updating by production measurements, time-lapse seismic data and other available data. Time-lapse seismic data helps to determine reservoir changes that occur with time and can be used as a new dimension in history matching since they contain information about fluid movement and pressure changes between and beyond the wells.

The well production schedule and history are provided for the period from Dec. 1997 to Dec. 2004 and comprise the observation data for the history match. A previous full field calibration was performed by the operator to match the history up until 2003. The reservoir attributes previously calibrated include fault transmissibility multipliers, regional relative permeability parameters, and large-scale (absolute) permeability and porosity heterogeneity using regional and constant multipliers, in total defining a global history match for a single (structural) reservoir description. The exercise was to improve the match and then perform a recovery optimization.

In total five groups participated in this exercise and four presented their results during the workshop (see Table 1). The limited number of participants was due to the inaccessibility of the Norne database (license limitation) to commercial companies.

<table>
<thead>
<tr>
<th>University/Company</th>
<th>Main Contributors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford University, Chevron &amp; IBM</td>
<td>Amit Suman, Drosos Kourounis, Tapan Mukerji and Khalid Aziz</td>
</tr>
<tr>
<td>Delft / TNO</td>
<td>Slawomir Szklarz, Lies Peters and Remus Hanea</td>
</tr>
<tr>
<td>Texas A&amp;M</td>
<td>Eric Bhark, Rey Alvaro, Mohan Sharma, Akhil Datta-Gupta</td>
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<tr>
<td>NTNU</td>
<td>Ola T. Miljeteig, Richard Rwechungura, Anass Ammar and Jon Kleppe</td>
</tr>
<tr>
<td>University of Texas Austin</td>
<td>Reza Tavakoli and Mary Wheeler**</td>
</tr>
</tbody>
</table>

**Did not present the results in the workshop

Description of the Norne Field
The Norne Field is located in the blocks 6608/10 and 6508/10 on a horst block in the southern part of the Nordland II area in the Norwegian Sea. The rocks within the Norne reservoir are of Late Triassic to Middle Jurassic age.

The present geological model consists of five reservoir zones. They are the Garn, Not, Ile, Tofte and Tilje. Oil is mainly found in the Ile and Tofte Formations, and gas in the Garn formation. The sandstones are buried at a depth of 2500-2700 m. The porosity is in the range of 25-30% while permeability varies from 20 to 2500 mD (Steffensen and Karstad, 1995; Osdal et al., 2006). The data consist of near, mid and far stack 3D seismic data acquired in 2001, 2003 and 2004. More information about the Norne field, provided data and first case release are given in Chapter 5 (Rwechungura et al., 2010).

The first package includes the E-segment of the Norne field; other benchmarks will include larger parts of the field. Further, the seismic data were also separated to suit the requirement of coverage of the E-segment only. Accordingly, the E-segment was chosen because it has the highest quality seismic data of the entire field. The E-segment of the Norne Field consists of 8733 active grids and 5 wells as of the end of 2004, i.e., 2 injectors and 3 producers. Participants were given a password to access the Norne database through the website www.ipt.ntnu.no/~norne.

Description of the Exercise
The exercise was defined six months prior to the workshop on History Matching and EOR optimization using both production and time lapse seismic data. This benchmark case considers the time frame from 1997 to 2004 for history matching and 2005 to 2008 for recovery optimization. The actual 2004 simulation model containing all information and properties was given. In addition, production and injection data from 1997 to the end of 2004, and 4D-seismic data for the same period (2003-2001 and 2004-2001) were
provided. These data are the basis for the history match performed by participants.

The following was the defined workflow:

- Download the Eclipse Norne model and import it into their reservoir simulator. The production history for 1997-2004, reports and all required data are given in the website http://www.ipt.ntnu.no/~norne.
- Participants were required to history match the model until the end of 2004 and predict the production (oil, water and gas rates) performance until end of 2008.
- Using the history matched results from above, create an optimal production strategy for the remaining recoverable resources for the future period. Participants might also suggest techniques to enhance recovery, since significant amount of the recoverable reserves were already produced by the end of October 2008.
- The format for the production strategy should contain time, pressure (BHP) or flow rates for the wells.
- The following constraints should apply to the strategy:
  1. For each injector well the maximum FBHP = 450 bar
  2. For each producer well the minimum FBHP = 150 bar
  3. For each injector well the maximum water rate = 12000 Sm$^3$/day
  4. For each producer well the maximum liquid rate = 6000 Sm$^3$/day
  5. Maximum water-cut = 95%
  6. A maximum of two wells can be sidetracked to increase recovery
- The following economic parameters were given:
  - Oil price 75 US$ per bbl
  - Discount rate 10% reference time is January 2005
  - Cost of water handling/injection 6 US$ per bbl
  - Cost of gas injection 1.2 US$ per Mscf (M = 1000)
  - Cost of a new side-tracked well 65 million US$

Participants could also assume their own parameters related to other EOR methods, e.g., surfactants, polymers and low salinity water flooding.

- Discuss and compare results of the achieved recovery factor.

General Methods for all the Groups
As stated before, four groups presented their results in the applied technology workshop in June 2011 in Trondheim. In this paper we present the details of the work from three groups, namely Texas A&M University, the Norwegian University of Science and Technology (NTNU) and Stanford University. The history matching results from TU Delft were previously published (Szklarz S et al. 2011). They used the Ensemble Kalman Filter (EnKF) method for history matching and did not perform an optimization or an enhanced oil recovery (EOR) strategy; therefore, this paper does report the results from TU Delft.

A summary of the methods applied for history matching and recovery optimization by each group is in Table 2. To perform history matching, Stanford University started by dimensionality reduction of the reservoir parameters using their principal component analysis (PCA) and then application of particle swarm optimization (PSO) for history matching. For subsequent optimization they used a derivative free method, Hook Jeeves Direct Search (HJDS). The group from Texas A&M first engaged in multiscale re-parameterization of the permeability field using the Grid Connectivity-based Transform (GCT) and calibrated the reduced permeability to production data using a Quasi-Newton method. Thereafter they applied a streamline-based method to integrate the 4D seismic data. Last, the Texas A&M group increased recovery and optimized the production forecast by first draining the oil pockets through side tracking, and by second applying a streamline-based method to equalize the arrival time of fluid phase fronts at all producers. The group from NTNU applied manual history matching techniques that included qualitative use of time-lapse seismic data. They then optimized production by oil pocket drainage through the addition of new wells and low salinity water flooding. The methodological details of each group are explained in Appendix A of this paper.

Table 2: Summary of methods by the groups.

<table>
<thead>
<tr>
<th>University/Company</th>
<th>HM Methods</th>
<th>Optimization/ EOR Strategies</th>
</tr>
</thead>
</table>
| Stanford University | -Dimensionality reduction using principal component analysis (PCA)  
  -Particle Swarm Optimization | Derivative free optimization – Hook Jeeves Direct Search (HJDS) |
| Texas A&M | -Multiscale re-parameterization of permeability field using Grid | -Oil pocket drainage through side tracking. |
Results and Discussion

As stated at beginning of this paper, there is no winner or loser in this case; no one exactly knows the answer. The outcome and experience are more useful. The group that attained the highest recovery factor also attained the lowest NPV increase because their methods to increase recovery included the more costly introduction of new wells. Although all of the groups used different strategies and methods, the results do not differ too much which indicates that the approaches applied may be realistic. A summary of the results is shown in Table 3.

Table 3: Results summary from each group Norne first case.

<table>
<thead>
<tr>
<th>University/Company</th>
<th>Incremental NPV ($10^6$ US$)</th>
<th>R.F (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stanford University</td>
<td>435</td>
<td>50.70</td>
</tr>
<tr>
<td>Texas A&amp;M</td>
<td>344</td>
<td>49.24</td>
</tr>
<tr>
<td>NTNU</td>
<td>303</td>
<td>52.20</td>
</tr>
<tr>
<td>Base Case</td>
<td>-</td>
<td>48.80</td>
</tr>
</tbody>
</table>

One of the main challenges in reporting the combined case study results is the different formats and notations used by the participants; this was because there was no specific guidance on how to present the results defined before for the beginning of the work. The participants’ specific notes about the methods and results are given in detail in Appendix A.

Conclusions

This paper summarizes the results of a unique case study on history matching and optimization methods tested using real field data. The provided data include 4D seismic data which enhanced the quality of the work performed. A workshop was organized by the IO Center and SPE to discuss the results whereby 80 delegates from different parts of the world attended. History matching methods are being developed through both field-specific studies and methodological research. The workshop provided an opportunity to address the state-of-the-art technologies within the area of optimization, focusing both on production history and 4D seismic data and the interplay between these two diverse types of data. The workshop was a success with active discussion and contributions from the beginning to the end. This serves as the first benchmark case study using data from the E-segment of the Norne field.

A single conclusion for the Norne field characterization and optimal production schedule has not been achieved; however, bringing together the suite of approaches applied was valuable. The use of seismic data in this case was not as expected; more use of seismic data, both qualitatively and quantitatively, is required in future cases. Because the case study was defined only six months prior to the workshop, most of the participants considered that the time provided was not enough and, therefore, advised that more time is required, up to a duration of one year, for future comparative case studies.
Appendix A: Participants own notes

A.1 Results from Texas A&M University, College Station, Texas USA

Eric Bhark, Rey Alvaro, Mohan Sharma, Akhil Datta-Gupta

A.1.1 History Matching

For this project we assume a deterministic approach to dynamic data integration and calibrate the single reservoir model to the production data over the complete history provided from 1997 to 2004, and also to time lapse seismic data over the interval from 2001 to 2003. Using the calibrated reservoir model, we then investigate different hypothetical production scenarios and, after selection of the most favorable scenario, perform optimization of the well injection and production rate schedule from Jan. 2005 to Dec. 2008. The structured workflow begins with calibration of the full field permeability heterogeneity, at grid cell resolution, to the production three phase rates using a multiscale heterogeneity re-parameterization. Because of the previous calibration performed by the operator, which defines the prior model in this application, our conceptual approach is to minimally update the permeability at only locations and scales required to improve transport paths within the reservoir induced by production, water injection and aquifer support, and to otherwise leave the prior unchanged. The calibration also requires adjustment of fluid contacts in the Garn formation (layers 1-3 of the reservoir model).

The seismic data are next integrated into the reservoir description as the time-lapse change in acoustic impedance. Integration as the change in, rather than magnitude of, acoustic impedance emphasizes the influence in the fluid evolution in the reservoir while at the same time reduces the influence of uncertainties in the static reservoir parameters that in part determine the rock elastic properties. The inversion is performed using semi-analytical, streamline-derived sensitivities of acoustic impedance at grid cell resolution to perturbations in absolute permeability. It is important to note that this sequential approach to production and seismic data integration is taken on account of the multiple sources of uncertainty and approximation associated with the seismic data definition, both observed and simulated. Regarding the former, there is uncertainty in the seismic data inversion from reflection amplitude to acoustic impedance, and also in the subsequent mapping of the high-resolution seismic image to the lower-resolution model grid cells. Regarding the latter, or computation of acoustic impedance at grid cells from simulated fluid phases and pressure, we consider only the influence of fluid saturations to define changes in rock elastic properties via a petro-elastic model (PEM).

In the final workflow component of production optimization, our objective is to obtain an optimal as well as accelerated injection and production rate strategy, where rates are characterized in terms of the streamline-based arrival time of fluid phase fronts at the producers. The optimal strategy maximizes sweep efficiency, and therefore recovery, by equalizing flood front arrival times at all producers within a well pattern. The acceleration strategy increases production and injection, subject to operational constraints, to decrease the arrival time and indirectly maximize NPV.

A.1.1.1 Production Data Integration

The production data history match is achieved by the calibration of the full field absolute permeability, at grid cell resolution, together with adjustment of the WOC in the Garn formation. Both approaches are described in this section. Consistent with our deterministic approach, a gradient-based minimization of production data misfit is performed by adjustment of the estimable parameters using a quasi-Newton method. The production data misfit is characterized by a three-term objective function that characterizes oil, water and gas production rates at the three producers, over the complete history from 1997 to 2004, with each term weighted by the inverse of the $l_2$-norm of the historical observations corresponding to each phase.

For calibration the permeability heterogeneity is re-parameterized using the grid-connectivity-based transform (GCT) method (Bhark et al., 2011), an approach of linear transformation where the heterogeneity is updated in a transform domain that is characterized by the spectral modes of the reservoir model grid. The change of basis from the spatial to spectral domain is performed by multiplication of the heterogeneity field with the GCT basis vectors. The parameterization enables the selective calibration of reservoir heterogeneity in a sequential manner, from the coarse to fine scale, using very few transform parameters that are used to weight the influence of each basis vector on the spatial field.

An individual GCT basis was constructed for the parameterization of each layer of the reservoir model. The vertical stratification of the prior permeability shows negligible correlation between most adjacent layers; therefore, the parameterization of each layer individually prevents the smoothing of high-resolution vertical variability that we wish to preserve. Figure A-1 shows a set of the leading GCT basis vectors mapped onto the grid for layer 1. Notice that the spatial variability depicted within each of the basis vectors characterizes large to finer scale detail, consistent with a modal frequency representation, and beginning with the lowest or zero frequency.

The multiscale history matching algorithm begins by updating the prior permeability model using a parameterized multiplier field that is superimposed onto the grid and assigned an initial value of unity at each cell. It is the multiplier that is sequentially refined from the coarse to finer scales during minimization of production data misfit, thereby permitting selective updating of heterogeneity at locations and levels of detail sensitive to the available data, and otherwise leaving the prior model unchanged as desired. Each of
the layers is initially parameterized using only its constant basis vector (see Figure A-1), resulting in only 22 parameters. It is from this parsimonious model description that the detrimental consequences of over-parameterization are diminished, namely non-uniqueness from parameter correlation and the inclusion of multiple insensitive parameters.

Following minimization of the objective function to a local minimum, the production data were found most sensitive to the mean permeability of only six model layers (2, 10, 19 – 22). The multipliers corresponding to all other layers effectively retained their initial value of unity throughout the inversion iterates, or were consistently observed to have a negligible contribution to the objective function gradient (to within a small tolerance). To continue with the calibration and following the approach of sequential refinement, basis vectors were next added to the parameterization of the six sensitive layers for the definition of 6 parameters per layer or 36 parameters in total. It is necessary to add basis vectors to the parameterization in sets because it is their linear combination that depicts heterogeneity. Another gradient-based minimization was performed, and upon convergence additional basis vectors were added to the parameterization of only layers 9 and 20; the production data were generally insensitive to refinement of the other layers. This two-step procedure of refinement and data misfit minimization was repeated once more, for a total of 71 parameters, at which point the data misfit was deemed acceptable and the calibration was terminated.

Figure A-2 shows the calibrated multiplier and permeability maps for five of the most sensitive layers, labeled with the number of GCT basis vectors used for their final parameterization. As intended, the updates are overall larger-scale, smooth and relatively minimal, thus accomplishing the objective of nominally updating the prior which was to some extent previously calibrated. The production data misfits are shown in Figure A-3 at the three producers. The improvement in the match at all three wells, and for all three phases, is satisfactory.

In addition to permeability adjustment, the history improvement at well E-3AH required lowering of the WOC in layers 1 through 3 from 2618.0 m to 2648.2 m TVD, increasing the oil rim by this difference. The initial oil and water phase rates at this well were grossly under- and over-predicted, respectively. The gas rate was approximately matched. In the simulation model, E-3AH has seven completion intervals in layers 1 and 2 that intersect the WOC. Therefore, adjustment of permeability, relative permeability or other transport parameters was unable to change the produced phase proportions. The well is fluid volume rate controlled in the simulation model, and because this net volume target was met, the evident choice to re-apportion the water and oil phase rates was to lower the WOC (via automated optimization). A cursory review of the Norne reservoir management documentation (New reservoir simulation model: Norne PL128) reported prior uncertainty and adjustment of the Garn fluid contacts, and their field-wide specification based on only two well surveys reported at 6608/10-3 and E-3H (to the knowledge of the authors’), so for the purpose of this analysis we propose that the Garn WOC calibration falls within the window of (qualitative uncertainty), although this result is clearly non-binding.

A.1.1.2 4D Seismic Data Integration

The seismic data integration begins with the inversion of the seismic volumes of reflection amplitude to changes in acoustic impedance, conditioned to acoustic impedance computed from sonic and density logs, which are mapped to the reservoir model grid. This analysis was performed by the research group of Dr. Gibson in the Texas A&M Geophysics department. The change in acoustic impedance between the time-lapse surveys at 2001 and 2003, at grid cell resolution, defines the observation data set to which we locally calibrate the reservoir permeability model.

The definition of data misfit for the seismic data integration requires the computation of simulated acoustic impedance at 2001 and 2003 based on the cell saturations and pressure. For this we use a PEM, defined by Gassman’s equations (Gassmann, 1951), that relates the fluid, solid rock and matrix elasticity to the saturated bulk modulus, where the matrix includes the effect of rock stiffness reduction caused by porosity. We further assume that the shear velocity is almost unaffected by changes in the pore fluid, and also assume a linear relationship between the frame bulk modulus and the porosity of the rock (Mavkov, 1998). The saturated bulk modulus is then used to compute acoustic impedance through the compressional velocity. With this, the calibration objective function is defined as the difference of the simulated and observed time-lapse acoustic impedance data changes over all cells that fall within the seismic cube. The data integration is performed through reduction of the objective function by refining permeability along flow paths that are shown to characterize fluid front movement from the injection wells and aquifer to the production wells, as described below. The objective function is additionally augmented with two regularization terms. These consist of a ‘norm’ and a ‘roughness’ constraint and have the effect of preserving the prior model (i.e., geologic realism) and spatial continuity in the permeability updates. When formulated as an augmented system of linear equations, an iterative sparse least-squares algorithm is used to solve the inverse problem.

At each iteration of the gradient-based inversion, the permeability update step is derived from the local sensitivity of the time-lapse acoustic impedance change at a given cell (Z) to a perturbation in the permeability field (k), or \( \partial Z / \partial k \). Using the chain rule this sensitivity can be expanded as

\[
\frac{\partial Z}{\partial S_w} \times \frac{\partial S_w}{\partial k}
\]

The first term or sensitivity is computed from numerical differencing using the
analytic form of the PEM. The second term is computed with an efficient streamline-based formulation that analytically relates the arrival time of a propagating water front and the reservoir properties (i.e., permeability in this application) through which the front traverses (Vasco et al., 2004). Using an asymptotic solution for the problem of the propagation of an incompressible two-phase front, the front saturation is defined as a function of (physical) time and the distance traveled along the front trajectory or streamline, which is known from the simulated velocity field. This coordinate transformation enables the expression of the equations governing fluid motion as a series of one-dimensional equations that are characterized by the time of flight along streamlines (Vasco and Datta-Gupta, 2001). The efficiency of the sensitivity formulation ($\partial S_w / \partial k$) then manifests as an analytical relationship between a perturbation in the fluid front saturation and its travel time, which by a chain rule operation is related to a perturbation of the permeability at all cells along the streamline, and requires only a single forward simulation for population of the sensitivity at all cells (Vasco et al., 2004). A final important consideration is that for this analysis we have extended the sensitivity formulation to account for variations in streamline geometry over the time-lapse interval that result from changing field conditions. For this we assume that saturation is characterized not only by time of flight, but also by the previous state of the saturation, or the (physical) times at which streamline geometries are updated using velocities from successive simulations.

Implicit in the above-described approach to seismic data integration is the focus on positive time-lapse changes in acoustic impedance that result primarily from the replacement of oil by water, or on processes fully accounted for in our formulation. The PEM and sensitivity formulation applied together are not used to account for pressure and gas effects. The results of this study, and previous investigations of seismic information in the Norne field (Osadal et al., 2006; El Ouair et al., 2005; Lygren et al., 2005), support our approach with the observation that the majority of observable changes in acoustic impedance over the E-segment are related to the displacement of oil by water. Figure A-4 presents a qualitative depiction of the history matching results following the production and seismic data integration. In this figure the modeled changes in water saturation on the grid, before and after seismic data integration, are (orthogonally) juxtaposed to the observed changes in acoustic impedance in the seismic volume. The apparent rise in the oil water contact over the time lapse interval, shown in two different grids transects, is well captured by the calibrated model and is consistent with the observed increase in acoustic impedance over this depth interval.

The improvement in the modeled transport behavior following calibration is more clearly observed when we compare the changes in acoustic impedance on a layer-by-layer basis. Figure A-5 shows the extent of the modifications in the acoustic impedance for selected layers. Even though the majority of the time lapse changes resolved are related to the replacement of oil by water (i.e., positive changes), there are noticeable locations of a decrease (red color) in acoustic impedance that are unrelated to water movement and that, we infer, are related to changes in pressure. These changes are located in areas that are initially fully saturated with water; therefore, the decrease in bulk modulus is not related to changes in fluid saturations at those cells, but rather to changes in the average pressure.

As the final step of the workflow we assess the quality of the history match of the production data, or at the well level. Figure A-3 shows the responses for the water, oil and gas production rates before and after the complete, structured calibration workflow. Although the production data were not included in the objective function for the seismic data integration, as intended the local permeability updates do not degrade the match quality.

### A.1.2 Optimal Production Strategy

#### A.1.2.1 Evaluation of Production Strategies

Prior to the optimization of well injection and production rates through the forecast period from Jan. 2005 to Dec. 2008, we investigated multiple production scenarios for definition of the single strategy for which the rate optimization would be performed. To begin with the most basic scenario, the calibrated reservoir model was used to make production forecasts to Dec. 2008. The wells were allowed to produce at their last voidage rates i.e., at Dec. 2004, for this ‘Do Nothing’ scenario under the constraints listed in the exercise description.

The various strategies evaluated included sidetrack wells (from E-2H, E-3H and E-3AH) through undrained regions of the E-segment, and the conversion of water injectors (F-1H and F-3H) to gas injectors. Of all combinations, we selected the combined strategy of a sidetrack in layer 10 from E-3H with conversion of water to gas injection in F-1H, which has a strong hydraulic connection with E-3H and E-2H (Figure A-6), as the ‘Base Case’ for rate optimization. Layer 10 has the highest remaining oil pore volume at Dec. 2004, and gas injection proved beneficial for NPV improvement because of the lower injection/production cost relative to water. The Base Case resulted in an increase in RF by 0.7% (to 48.5%) and in NPV by 872 MMS over the scenario of production at the Dec. 2004 voidage rates using the original well pattern.

#### A.1.2.2 Rate Optimization

The optimal rate strategy is developed with the objective of (1) maximizing sweep efficiency by equalization of the (water, gas) flood front arrival time at all producers and (2) by enforcing an accelerated
rate strategy for NPV improvement. The objective function consists of the following two terms (Taware et al. 2010):

\[
f(q) = \sum_{i=1}^{N_p} (t_d(q) - t_i(q))^2 + \eta \sum_{i=1}^{N_p} (t_i(q))^2.
\]  

(A-1)

The variable \( t_i \) is the calculated front arrival time (or time of flight) at production well \( i \), and the desired arrival time \( t_d \) is given by the arithmetic average of \( t_i \) over all \( N_p \) wells during each optimization iteration (Alhuthali et al. 2010). The vector \( q \) contains the control variables and has a dimension of \( N_p \).

Minimization of the first term of Eq. (A-1) ensures that the flood front arrives nearly at the same time within the well pattern, thereby maximizing sweep efficiency (Sudaryanto and Yortsos 2001; Alhuthali et al. 2007; 2008; 2010). The second or acceleration term ensures that the magnitude of the arrival time is also reduced, with the effect of accelerating injection/production rates, and ensures that the optimization doesn’t over-penalize highly productive wells in the attempt to improve sweep. By adjusting the weight \( \eta \) on the penalty term, the trade-off between equalizing arrival time and accelerating injection/production is defined.

After (water and gas) front breakthrough, the optimization is performed by incorporating the phase cuts into the objective function so as to reduce the allocation of high production rates to wells with high water or gas cuts. To accomplish this, the arrival time to a well is modified to include the water cut at the well as

\[
t_i'(q) = t_i(q) \times (1 - f_{w,i})^\alpha.
\]  

(A-2)

In the above expression, the arrival time, \( t_i \), at well \( i \) is re-scaled to incorporate the well water cut, \( f_{w,i} \). If the water cut is zero, the modified arrival time is the same as the original arrival time. When the water cut at the well is greater than zero, the original arrival time is reduced so that this well has less of an influence in the objective function. The extent of reduction is controlled by the exponent term, \( \alpha \), which we set at 0.5 for this analysis. A similar modification is done to the arrival time after gas breakthrough.

The objective function is reduced, or the optimization of rates characterized by Eq. (A-1), is performed using a streamline-based workflow with five primary components. These are: (1) forward finite-difference flow simulation with the calibrated reservoir model for computation of \( t_i \) between injectors to producers (Datta-Gupta and King 2007) along streamline trajectories traced through the reservoir velocity field (Jimenez et al. 2008), (2) computation of the objective function as Eq. (A-1), (3) analytical computation of rate sensitivities defined as the partial derivative of a front arrival time with respect to well rates, (4) computation of the gradient and Newton approximation to the Hessian of the objective function and (5) minimization of the objective function using a Sequential Quadratic Programming (SQP) technique (Nocedal and Wright, 2006) to generate the required updates in rates subject to field constraints.

In this analysis the above steps are repeated over six-month intervals from Jan. 2005 to Dec. 2008. Rather than focusing solely on the E-segment wells, the optimization of the Base Case is performed on the full-field model. A streamline-based analysis of the flow connectivity revealed that injection/production in the E-segment influences, and is influenced by, wells and the aquifer outside of the E-Segment. Figure A-6 shows the reservoir flow pattern at Dec. 2004. In particular, E-3AH is connected to the aquifer outside of the E-segment, injection at F-1H supports E-2H and E-1H, and F-3H supports B-3H and D-2H.

A.1.3 Results

The improvements in recovery factor (RF) and net present value (NPV) from rate optimization in the Base Case are shown in Figure A-7a and A-7b, respectively. When the acceleration term is ignored, the arrival time equalization results in a delayed gas breakthrough (from injection at F-1H) at wells E-2H and E-3H-sidetrack, therefore increasing RF and NPV. It should be noted that in the Base Case without optimization, gas injection at F-1H causes wells E-2H and E-3H-sidetrack to shut-in in Feb. 2008 and Feb. 2007, respectively, when the maximum GOR is reached. Although detrimental to RF relative to the case when water is injected at F-1H, the lower gas injection & processing costs relative to water result in an increase in NPV that outweighs any oil production loss from the shut-ins. This offset in NPV only improves after the optimization.

As the acceleration term is included in the optimization and its influence increased, the improvement in RF is reduced as the injection and production rates are increased and the delay in gas breakthrough at E-2H and E-3H-sidetrack is lost. However, the increased rates still result in a minor increase in RF that outweighs this loss. Additionally, an unintended benefit is observed that is related to the improved role of field pressure support by the gas injector. As the gas injection rate increases with the acceleration term, the maximum well pressure constraints in several distal water injectors are approached and result in decreased injection rates relative to the gas rate at F-1H. This disproportionately improves NPV (Figure A-7b)
because of the lower gas costs relative to water injection/production. To conclude, there is ultimately a tradeoff in RF and NPV determined by the degree of inclusion of the acceleration term. Larger recovery factors are associated with a more equalized sweep in terms of (water and gas) arrival time; however, to achieve a maximum NPV with this strategy requires a longer forecast period, in this case well beyond Dec. 2008. Although the rate increases or acceleration attempts to balance these metrics, as we have demonstrated, it also stresses the system and increases the complexity of the optimization (e.g., resulting in well shut-ins).

A.2 Results from NTNU
Richard Rwetchungura, Ola T. Miljeteig, Anass Ammar and Jon Kleppe

A.2.1 Summary
An approach for integrating 4D seismic data in the history matching process alongside with the traditional utilization of production data is proposed. The proposed approach is applied on an Eclipse 100 black oil model of the E-segment in the Norne Field with success. The discrepancy between the observed production data and the simulated production data is heavily decreased, and simulated OWCs shows similar trends as OWCs interpreted from two 4D datasets. Several potential history matched models which showed good match between observed and simulated production data were disregarded because of the OWCs from the 4D seismic data. Still, there are uncertainties related to the general fluid flow patterns in the reservoir, and a more extensive utilization of 4D seismic data is encouraged, regardless of it being qualitative or quantitative utilization. Furthermore a manual production optimization process on the simulation model of the Norne field E-segment was carried out. The existing development scheme was revised and several potential well targets were tested. The simulated recovery in the E-segment was increased from 48.8% to 52.2% and the predicted NPV of the E-segment was increased from 676 million US$ to 979 million US$ by adding an additional production well. The simulated recovery was further increased to 52.8% by adding an additional injection well, but the drilling cost and increased water injection costs rules out an additional injection well as a feasible investment. Low-salinity water flooding has been simulated with limited success. The mixing of low-salinity and high-salinity water is evident and more oil is mobilized in the simulation model, but the prediction period is too short for the mobilized oil to reach the production wells. Further studies on low-salinity injection on the Norne Field are encouraged.

A.2.2 History Matching
The history matching approach used in this work is a modification of the traditional manual history matching approach. The seismic data is taken into consideration by adding interpreted OWCs from two seismic surveys (2001 and 2004) as a matching parameter. Practically speaking, it proved hard to match the OWC alongside the production data, resulting in the history matching loop shown in Figure A-8. The main matching parameters were oil production rates and water-cuts in the production wells in the E-segment, as well as the OWCs derived from the seismic data. In addition to the main matching parameters, theGOR and BHP of the production wells were monitored and used for validation.

A.2.2.1 Time Lapse Seismic Data
Changes in fluid saturations and pore pressures which characterize 4D surveys has been monitored most prolifically in classic hydrocarbon reservoirs. To effectively recognize the changes which time-lapse survey bring we can analyse changes in amplitude or travel-time changes as shown in Figure A-9 (Landro 2010). Time-lapse surveys have also been used extensively in the identification of OWC. In the E-segment of the Norne field, 4D surveys have been carried out often and thus the interpretation of the OWC in this field which is confirmed by pilot well drilled within these periods confirms the viability of the OWC interpretation.

Procedures for determining OWC in 4D seismic using Seisworks and Petrel: The 4D difference cube as well as the base and monitor surveys (2001 and 2004) were loaded and the reservoir was identified from the seismic section with the help of geological reports and available well logs. Line 1050 in Figure A-10 was selected from the set of seismic lines for interpretation due to its good quality. The inline and cross lines traces which go across this line were checked to make sure that the structure was representative. The identified OWC from the section was combined with the model using petrel as a platform as indicated in Figure A-11. After the interpretation the OWC was compared with that from Statoil (Figure A-12) and this was extrapolated to the reservoir model.

A.2.2.2 History Matching Process
Several parameters were pretty uncertain in the simulation model, including (but not limited to) vertical permeabilities in the Ile and Tofte Formations, vertical transmissibilities between several layers and the transmissibility through a major fault (E01) going through the segment of study. Figure A-13 shows the impact some of the uncertain parameters have on the water-cut in one of the production wells (E-2H).

A.2.2.3 History Matching Results
The match with the production data from the E-2H well is greatly improved (Figure A-14). The water breakthrough is at the right time and the general water-cut trend is well matched apart from the end of the history, where the fluctuations proved hard to match. The match with the production data in the E-3H and E-3AH wells are also improved (Figure A-15 & Figure A-16)

The Oil-Water-Contacts interpreted from the seismic surveys of 2001 and 2004 is shown on the simulation grid on respective dates in Figure A-17. The OWC from 2004 was matched very well, whereas the survey from 2001 proved hard to match. With the vertical flow barriers in the simulation model the water rises to slow, and fails to reach the level of the 2001 seismic survey.

### A.2.3 Production Optimization

Attempts were made to recover as much of the remaining oil as possible (Figure A-18), using a manual approach. Several potential well targets were tested and the well rates were tweaked to increase the NPV. Table A-1 shows the best cases with 0, 1 & 2 sidetracks. Both the NPV and the recovery factor were increased considerably in the simulation model. The wells were placed to try to drain the most obvious remaining oil in the simulation model, and then the NPV was maximized by tweaking the well placements manually in the chosen area. The well rates were manually tweaked, also to maximize NPV. Low-salinity waterflooding was simulated with limited success. Table A-2 shows the results of the simulation of the low-salinity waterflooding, and according to the results no extra recovery should be anticipated.

### A.2.4 Discussion

The main objective was to qualitatively use 4D seismic data to enhance our history match, this was done by matching the OWC from the interpreted OWC from 2001 seismic data to the modeled OWC from production data. To match the mentioned OWC proved very challenging, but there are a couple of uncertainties worth mentioning. Firstly, the seismic data originate from the time domain so that the exact position of the seismic OWC on the simulation grid is uncertain. Also, the seismic line chosen is not parallel to the simulation grid, probably resulting in more deviation. Despite this, we regard the seismic OWC as a good tool for evaluating the trend of the movement of the OWC in the Norne reservoir.

Reasons for the problems matching it might be sub seismic faults, or perhaps limited areal extension of the vertical flow barriers observed in the cores and the pressure measurements. These would be factors that could lead to a faster rise in the OWC than the simulation model would anticipate.

The final history match in this study was chosen based on mainly experience and intuition. Therefore there are quite many uncertainties related to the quality of the model. As Figure A-19 shows, several different models show almost equal response on the water-cut of well E-2H. The similarities can be seen on the other production plots as well; i.e. there are several models giving almost the same match with the production data even though they are pronouncedly different. The OWCs used in this thesis helped reduce the uncertainties to some extent by invalidating some of the potential models, but even still there are a range of models which match the production data and the OWCs to the same degree. Using even more OWCs from seismic data in the history matching loop, could have invalidated even more models, but because of time issues only one cross-section from two surveys (2001 and 2004) were used. Also inverted saturations and pressures from 4D seismic data should help in categorizing major fluid flow patterns.

Even though the interpreted OWC helped reduce the amount of plausible models, there are still uncertainties related to the fluid flow patterns in the reservoir. The area with the obvious remaining oil in the used model (Figure A-18) does not contain the same amount of oil in all plausible models. This has resulted in considerable uncertainties related to the well pattern optimization of this work.

The validity of the results of the low-salinity study is very uncertain. There are huge uncertainties related to the relative permeability curves used (Figure A-20 and Figure A-21), as these were made mainly based on the work by Jerauld et al., 2006 on other reservoir rocks. Also, it is evident that low-salinity water mobilizes more oil, but the injection period needs to be extended to see any results.

### A.3 Results from Stanford University

Amit Suman, Drossos Kourounis, Tapan Mukerji and Khalid Aziz

#### A.3.1 History Matching

Time lapse seismic has evolved as an important diagnostic tool in efficient reservoir characterization and monitoring. In combination with geological and flow modeling as a part of history matching process it can provide better description of the reservoir and help with the problem of history matching. In this study we jointly match time-lapse seismic and production data of segment E of Norne field. Recently stochastic optimization based inversion has shown good results in integration of time-lapse seismic and production data in reservoir history matching. We have used spatial principal component analysis for parameter reduction, and particle swarm optimizer (PSO) for inversion of segment E of Norne field data set.

#### A.3.1.1 Time-lapse Seismic Data Integration

Time lapse seismic data can be used as an important tool in reservoir characterization, monitoring and management. It can provide information on the dynamics of fluids in the reservoir based on the relation
between variations of seismic signals and movement of hydrocarbons and changes in formation pressure. Movement of fluids and changes in pore pressure depends on the petrophysical properties of the reservoir rock. Thus reservoir monitoring by repeated seismic or time-lapse surveys can help in reducing the uncertainties attached to reservoir models. Reservoir models, optimally constrained to seismic response as well as flow response can provide a better description of the reservoir and thus more reliable forecast.

Huang et al., (1997, 1998) formulated the simultaneous matching of production and seismic data as an optimization problem, with updating of model parameters such as porosity. Walker and Lane (2007) presented a case study that included time-lapse seismic data as a part of the production history matching process, and show how the use of seismic monitoring can improve reservoir prediction. It is difficult to obtain a global optimum match of production as well as seismic data using conventional gradient based optimization methods (Sen and Stoffa, 1996). Stochastic optimization based inversion methods have shown advantages in integration of production and time-lapse seismic data in reservoir history matching (Jin et al, 2007, 2008). Particle swarm optimization has been used in a variety of optimization and inverse problems in different branches of engineering and technology (Polli, 2008b), as well as in geosciences (Shaw and Srivastava, 2007; Fernández-Martínez et al., 2008b; Naudet et al., 2008; Yuan et al., 2009; Fernández-Martínez et al., 2009). Recently it has been used to optimize well types and locations (Onwunalu and Durlofsky, 2009). Fernández Martínez et al (2010) have used particle swarm optimizers to invert production data and time lapse tomographic data for a synthetic study. In this study we use the CC-PSO (García Gonzalo and Fernández Martínez, 2010) as global optimizer for integration of production and time-lapse seismic data in history matching for the data set of Norne field. Particle swarm optimization (PSO) is well described in chapter 4 of this thesis.

A.3.1.2 HM Methodology
The methodology does not only consist in looking for the model of minimum misfit, but also to find the family of models belonging to $M$ that fit the observed data ($d \in \mathbb{R}^n$) comprising all the observables, e.g. production and/or seismic data) within the data error tolerance ($\|F(m) - d\|_2 \leq tol$). This family will be used to estimate the porosity and the permeability of the reservoir as it has been shown in Fernández Martínez et al (2010), for the Stanford VI shale and sand reservoir. In our case the forward model has multiple components, a reservoir flow simulator to predict the production data, forward seismic modeling, a geostatistical model to constrain the spatial structure of the reservoir, and finally a rock physics model that takes into account relations between porosity, fluid saturations, and elastic velocities. We vary several parameters to get a good history match. These parameters include spatial distribution of porosity, relative permeability curves, pore compressibility, oil water contact, gas oil contact, fault transmissibilities and vertical transmissibilities.

We perform dimensionality reduction using the spatial principal component base (Echeverria and Mukerji, 2009, Echeverría et al., 2009, Fernandez Martinez et al, 2010). This reduction allows us to perform sampling on the reduced model space using global optimization algorithms. This reduction is also aimed at regularizing the inverse problem since the high frequencies on the model might not be informed by the observables. One thousand realizations of porosity field are generated using sequential Gaussian simulation (SGSIM) conditioned to the well data and variograms. Corresponding one thousand permeability fields are generated based on the relationship between porosity and permeability in different zones. These one thousand realizations are used to perform spatial PCA and get the reduced base by selecting seventy major principal components compared to 8733 cells in the reservoir model. We optimize a total of ninety-nine parameters using CC-PSO for joint inversion of time-lapse and production data of Norne field. These ninety-nine parameters include seventy PCA coefficients, pore compressibility, relative permeability, oil water contact, gas oil contact, fault transmissibilities and vertical transmissibilities of the layers. The objective function consists of sum of misfit of production and seismic data. The production data misfit consists of normalized L_2 norm of difference between modeled and observed production data. The seismic data misfit is the difference between relative root mean square amplitude change on top of the E-segment between 2001 and 2004 in the observed and modeled seismic data. The relative root mean square amplitude change on top of the E-segment between 2001 and 2004 for observed data is equal to 10.7.

A.3.1.3 HM Results
Figure A-22 shows the production response of observed and best history matched model. We obtained a very reasonable history match for all the wells except E-3A. The relative root mean square amplitude change on top of the E-segment between 2001 and 2004 for the best history matched model is 9.1 (reasonably close to that of observed seismic data i.e. 10.7). Figure A-23 compares the best history matched model with the provided model. We see more heterogeneity in permeability and porosity distribution of best history matched model as compared to the provided initial model.

A.3.2 Optimization
We study two different optimization scenarios. The first maximizes the net present value (NPV), while the
Let $J$ be the objective function. The optimal control problem in each case reads:

Maximize \[ J = \sum_{n=1}^{N} \frac{\Delta t_n}{(\alpha + 1)T_n} \left( e^\alpha q_n^0 - e^\alpha (q_n^{\text{inf}} + q_n^{\text{sup}}) - e^\beta q_n^0 \right) \]

subject to \[ g_n(x_n, x_{n-1}, u_n) = 0, \quad x_0 = x(t_0), \]

and \[ c_1 \leq c(x_n, u_n) \leq c_2, \] (A-3)
where $\Delta t_n$ is the time step length, $T_n$ is the time of the $n$-th time step measured in years, $\alpha$ is the discount factor, $q_{wi}$, $q_{wp}$, $q_{gi}$ are the rates of water injection, water production and gas injection at the $n$-th time step. The nonlinear equality constraints $g_a = 0$ with the initial conditions $x_0$ are the reservoir equations describing the physics of the flow in porous media, while the nonlinear inequality constraints $c$ are mathematical interpretations of operational or economic constraints that the optimal solution should fulfill. For the first optimization problem where the objective is the NPV, the coefficients $(c_0, c_w, c_g, \alpha)$ are given in Table A.3. For the second optimization problem, where we are interested in oil recovery, all coefficients are zero except $c_0 = 1$.

A.3.2.1 Controls
The optimization period considered here, starts on the 1st of January 2005 and ends on the 31st of December 2008. It is splitted in eight control periods of six months each. At each control period the bottom hole pressures (BHPs) of the wells are allowed to vary independently giving rise to forty control parameters that have to be tuned so that the objective of interest is maximized for each one of the cases considered.

A.3.2.2 Constraints
The nonlinear constraints $c$, for both optimization problems we will present, involve upper and lower bounds on the BHPs of the wells, up-per bounds on the injection and production rates and an upper bound on the water cut of each producer. Details about the upper and lower bounds of the constraints are given in Table A.4.

A.3.2.3 Gradient free optimization
For the optimization we employed the Hooke-Jeeves direct pattern search algorithm which does not require any gradient information. A maximum number of 3000 iterations were specified and the radius was set to 0.5. The objective is expected to be optimal at the end of the simulation time, but this is not guaranteed to be true at any other time during the simulation.

A.3.2.4 Nonlinear constraints
For the simulation of the flow in the reservoir, we used the commercial simulator Eclipse100. The nonlinear constraints are enforced by the simulator as follows: whenever the pressure (BHP) constraint is violated at an injector well, the simulator switches the injector from BHP control to rate control, keeping the rate of water injection at its upper bound and vice versa. The process for the constraints of the producers is similar, with water injection rate replaced by total surface liquid rate and the upper bound of the BHP for the injectors replaced by the lower bound of the BHP for the producers. Moreover whenever one of the producers exceeds the upper bound for the water cut, then the simulator will shut that producer.

A.3.2.5 Optimization Results
The convergence history of the Hooke-Jeeves direct pattern search algorithm is shown in Figure A-24 the blue line corresponds to the case where we optimize the NPV, while the red line to the problem where the objective of the optimization is oil recovery.

The base case for our optimization problem, assumes that the injector wells are operating on the maximum BHP (450 bar) and the producer wells at the minimum BHP (150 bar). Moreover, the simulator will enforce the nonlinear constraints during the simulation. This is also the initial guess for the optimization. We also consider the reactive approach, which is similar to the base case, with the only difference that the value of maximum water cut has been modified, so that the simulator will shut off the connections of a well that violate the maximum water cut only when the production of that connection does not increase the net cash flow. The reactive case usually provides slightly higher NPV than the base case where the water cut does not take into consideration the economic parameters or when there is no water cut constraint at all. The upper bound for the water cut for the reactive case was set to 92.6%.

The optimized NPV as a function of simulation time is shown in Figure A-25. The black line corresponds to the base case. The blue line corresponds to the NPV obtained from the optimal case. The red line corresponds to the case where we optimize oil recovery instead of the NPV. The green line corresponds to the NPV obtained with the reactive approach. We can see that the reactive approach has almost identical performance in terms of the NPV in all but the last control period. This is due to the fact that the modified water cut constraint unlike the original water cut constraint, is violated during the second half of the last control period instructing the simulator to stop the production of these wells. We also observe that when the objective is oil recovery, the final NPV is still much higher than the one obtained by the reactive approach but still much worse than the NPV obtained when we optimize the NPV directly.

In Figure A-26 we plot the oil recovery as a function of time. Again the black line corresponds to the base case which is the same one described above. The blue line corresponds to the case where we optimize NPV instead of recovery and the red line corresponds to the case where the objective that is optimized is oil recovery. Once again the green line shows the recovery obtained when we use the
reactive approach. We observe that the recovery obtained with the base case is already almost optimal and the optimized solution obtained higher recovery only by 2.9%. When we use the reactive approach the recovery is reduced by 1.7% from the base case and when we optimize NPV the recovery is reduced by 4.4% from the base case. That indicates that the NPV was maximized not by increasing the oil recovery, but by sufficiently reducing the amount of the injected and produced water. Indeed, if we plot the water injection for the base and optimal cases for the problem when we optimize NPV in Figure 6-28 we will see that the injectors are shut for most of the first three years and they start inject only during the last year. As a result the production of water which along with the injected water decrease the NPV, is considerably less than that of the base case, as we can see in Figure 6-29. In Figure 6-30 we plot the oil rates for both cases. Tables 6-6 and 6-7 summarize the percent increase of the NPV and oil recovery correspondingly for both optimization cases considered.

A.3.3 Conclusions and Future work

Particle swarm optimization method is applied for joint inversion of time lapse seismic and production data of Norne field. Next step is to explore different versions of PSO specially PP-PSO and CP-PSO, and to explore individually the impact of production versus seismic data on the overall model update. In future either seismic attributes or seismic interpreted properties would be compared over the whole reservoir model.

The optimization of the Net present value of the E-segment of the Norne field with BHP controls, revealed that significant increase of the NPV can be achieved if the injectors are shut for the first 3 years. However, oil production is decreased by this strategy and the increase of the NPV is entirely due to fact that the injected and produced water have been decreased considerably. The optimization of the oil production on the other hand increased the produced oil only marginally 2.9% over the base case. This suggests that more sophisticated oil recovery techniques are needed other than water flooding to extract the remaining oil from the E-segment.

**Tables and Figures**

**Table A-1: Prediction cases.**

<table>
<thead>
<tr>
<th>Case name</th>
<th>Extra producer</th>
<th>Extra Injec.</th>
<th>RF (%)</th>
<th>NPV US$ (10^6)</th>
<th>NPV US$ (10^9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRED11 (base)</td>
<td>NO</td>
<td>NO</td>
<td>48.82</td>
<td>6.85</td>
<td>675.7</td>
</tr>
<tr>
<td>PRED_PROD19</td>
<td>YES</td>
<td>NO</td>
<td>52.24</td>
<td>8.96</td>
<td>978.6</td>
</tr>
<tr>
<td>PRED_PROD_INJ</td>
<td>YES</td>
<td>YES</td>
<td>52.78</td>
<td>8.86</td>
<td>625.4</td>
</tr>
</tbody>
</table>

**Table A-2: Results of low-salinity flooding.**

<table>
<thead>
<tr>
<th>Case name</th>
<th>RF (%)</th>
<th>NPV US$</th>
<th>LOWSAL</th>
<th>BASE</th>
<th>LOWSAL*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BASE</td>
<td>LOWSAL</td>
<td>BASE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRED11 (base)</td>
<td>48.82</td>
<td>48.81</td>
<td>675 670 079</td>
<td>675 356 482</td>
<td></td>
</tr>
<tr>
<td>PRED_PROD_INJ</td>
<td>52.78</td>
<td>52.80</td>
<td>625 409 650</td>
<td>623 645 930</td>
<td></td>
</tr>
<tr>
<td>PRED_PROD_INJ_ALT2</td>
<td>52.61</td>
<td>52.82</td>
<td>486 220 865</td>
<td>519 507 778</td>
<td></td>
</tr>
</tbody>
</table>

*No investment costs or additional operational costs for low-salinity flooding included in calculations. Only included income due to oil production and expenses due to water injection (Assumed equal to high-salinity injection)*

**Table A-3: Economic parameters used for the definition of the net present value.**

<table>
<thead>
<tr>
<th>Economic parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil price co :</td>
<td>$75 per barrel</td>
</tr>
<tr>
<td>Water injection/handling cw :</td>
<td>$6 per barrel</td>
</tr>
</tbody>
</table>
Gas injection \( cg \): $1.2 \text{ per Mscf}

Discount factor \( \alpha \): 10% from January 1st

Table A-4: Upper and lower bounds on the BHPs for the injectors and the producers, maximum water injection rates and maximum liquid production rates as well as the water cut.

<table>
<thead>
<tr>
<th>Nonlinear constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Injection BHP</td>
</tr>
<tr>
<td>Production BHP</td>
</tr>
<tr>
<td>Water injection rate</td>
</tr>
<tr>
<td>Liquid production rate</td>
</tr>
<tr>
<td>Water cut</td>
</tr>
</tbody>
</table>

Table A-5: Net present value achieved when we use the base case, when we optimize directly the NPV, when we optimize the oil recovery and when we use the reactive approach. All the values are in billion dollars.

<table>
<thead>
<tr>
<th>NPV $10^9$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
</tr>
<tr>
<td>NPV</td>
</tr>
<tr>
<td>Oil recovery</td>
</tr>
<tr>
<td>Reactive</td>
</tr>
<tr>
<td>2.099</td>
</tr>
<tr>
<td>3.316</td>
</tr>
<tr>
<td>58%</td>
</tr>
<tr>
<td>2.534</td>
</tr>
<tr>
<td>21%</td>
</tr>
<tr>
<td>2.162</td>
</tr>
<tr>
<td>3%</td>
</tr>
</tbody>
</table>

Table A-6: Oil recovery achieved when we use the base case, when we optimize directly the NPV, when we optimize the oil recovery and when we use the reactive approach. All the values are in million sm3.

<table>
<thead>
<tr>
<th>Oil recovery Msm3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
</tr>
<tr>
<td>NPV</td>
</tr>
<tr>
<td>Oil recovery</td>
</tr>
<tr>
<td>Reactive</td>
</tr>
<tr>
<td>14.59</td>
</tr>
<tr>
<td>13.95</td>
</tr>
<tr>
<td>-4.4%</td>
</tr>
<tr>
<td>15.01</td>
</tr>
<tr>
<td>2.9%</td>
</tr>
<tr>
<td>14.34</td>
</tr>
<tr>
<td>-1.7%</td>
</tr>
</tbody>
</table>

Figure A-1: Parameterization of the permeability multiplier field (for layer 1) as the weighted linear combination of leading GCT basis vectors.
Figure A-2: The permeability multiplier fields (top) calibrated to production data and which, when multiplied with the prior model on a cell-by-cell basis, define the full-field permeability model (bottom).

Figure A-3: Production data misfit corresponding to the reservoir model after the sequential calibration to the production and 4D seismic data.
Figure A-4: A qualitative comparison of the pre- and post-seismic data integration results. The time-lapse changes in water saturation in two slices of the simulation grid are juxtaposed with perpendicular slices of the seismic volume that depict positive changes in acoustic impedance over the time lapse interval.

Figure A-5: Changes in acoustic impedance on a layer-by-layer basis for the initial, observed and the calibrated model.

Figure A-6: Well connectivity and flow patterns in the calibrated reservoir model identified by streamlines traced through the velocity field (at grid cell resolution) at the end of the production history (Dec. 2004).

Figure A-7: (A) RF for the calibrated field model ‘Base Case’ corresponding to sweep efficiency maximization (norm weight = 0) and production acceleration (norm weight = 100, 1000). (B) Incremental NPV over the ‘Base Case’ corresponding to the maximum sweep efficiency (norm weight =
0) and production acceleration (norm weight = 100, 1000).

Figure A-8: History matching approach used in this work.

Figure A-9: Shows the two 4D analysis techniques (Landrø 2010)

Figure A-10: Location of Seismic line 1050.
Figure A-11: Seismic and reservoir properties data integration using Petrel.

Figure A-12: Interpreted seismic line 1050. The yellow horizon represents OWC from 2001, the red one - OWC from 2004 (Statoil)

Figure A-13: Water-cuts in E-2H showing the effect of modification of several reservoir parameters.
Figure A-14: Water-cut in E-2H in the final history match vs. the base case.

Figure A-15: Water-cut in E-3H in the final history match vs. the base case.
Figure A-16: Water-cut in E-3AH in the final history match vs. the base case.

Figure A-17: Simulation grid overlain by the interpreted OWC from the seismic surveys of 2001 and 2004.
Figure A-18: Base prediction case without sidetracks @ 1st Jan 2009, showing considerate amounts of remaining oil.

Figure A-19: Illustrating simulated water-cuts (Well E-2H) for several decently history matched models.
Figure A-20: Example of the relative permeabilities for high-salinity (HS) and low-salinity (LS) water.

Figure A-21: Example of the fractional flow curves for high-salinity (HS) and low-salinity (LS) water.
Figure A-22: Comparison of production response of best history matched model and observed data.

Figure A-23: Porosity and permeability distribution of best history matched model.
Figure A-24: Convergence history of the Hooke-Jeeves algorithm, for both optimization scenarios. Blue corresponds to the case where NPV is optimized while red to the case where the objective is oil recovery.

Figure A-25: Net present value achieved for each one of cases considered. The black line corresponds to the base case, the blue line to the optimization of NPV, the red line to the optimization of oil recovery and the green line to the reactive approach.
Figure A-26: Recovery achieved for each one of cases considered. The black line corresponds to the base case, the blue line to the recovery obtained when we optimize the NPV, the red line to the optimization of oil recovery and the green line to the reactive approach.

Figure A-27: Water injection rates for the base case (left) and the solution which provides maximum NPV (right).

Figure A-28: Water production rates for the base case (left) and the solution which provides maximum NPV (right).
Figure A-29: Oil production rates for the base case (left) and the solution which provides maximum NPV (right)

References


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