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Enhanced heavy oil recovery for carbonate reservoirs integrating cross-well seismic – a synthetic Wafra case study

Klemens Katterbauer, Santiago Arango, Shuyu Sun, Ibrahim Hoteit

Earth Science & Engineering Program, King Abdullah University of Science and Technology, Saudi Arabia
Corresponding author: Klemens.Katterbauer@gmail.com, +966 544 701 630

Heavy oil recovery has been a major focus in the oil and gas industry to counter the rapid depletion of conventional reservoirs. Various techniques for enhancing the recovery of heavy oil were developed and pilot-tested, with steam drive techniques proven in most circumstances to be successful and economically viable. The Wafra field in Saudi Arabia is at the forefront of utilizing steam recovery for carbonate heavy oil reservoirs in the Middle East. With growing injection volumes, tracking the steam evolution within the reservoir and characterizing the formation, especially in terms of its porosity and permeability heterogeneity, are key objectives for sound economic decisions and enhanced production forecasts. We have developed an integrated reservoir history matching framework using ensemble based techniques incorporating seismic data for enhancing reservoir characterization and improving history matches. Examining the performance on a synthetic field study of the Wafra field, we could demonstrate the improved characterization of the reservoir formation, determining more accurately the position of the steam chambers and obtaining more reliable forecasts of the reservoir's recovery potential. History matching results are fairly robust even for noise levels up to 30 %. The results demonstrate the potential of the integration of full-waveform seismic data for steam drive reservoir characterization and increased recovery efficiency.

Index Terms— Heavy Oil, Steam Drive, History matching, Full Waveform Seismic, Ensemble Kalman Filter

I. INTRODUCTION

Heavy oil reservoirs have in the last decade encountered growing interest in the industry. As with the rapid depletion of the world's largest light oil reservoirs, heavier hydrocarbon components remain in the subsurface, which account for a considerable percentage of the oil in place [1]. Increasing demand from emerging markets has driven up the price for oil and gas, making heavy oil reservoirs commercially viable. Heavy oil reservoirs are typically found in shallower depths and therefore are easier to access than conventional reservoirs. However, their high viscosity and sulphur content make it more difficult and expensive to extract and process [2]. The high viscosity of heavy oil makes it rather immobile and challenging to displace via standard water injection. While tar sand recovery in Canada is performed via mining techniques [2], [3], heavy oil reservoirs typically use thermal methods to reduce the viscosity of the oil through heating. Amongst these, steam assisted cyclic gravity drainage and the earlier cyclic steam

stimulation technique are the most efficient and frequently employed for recovering heavy oil [4]–[8]. Steam injection into reservoirs exploits the increase in the temperature of the formation in order to reduce the viscosity of the heavy oil, and via pressure support enhances the oil's mobility. Increasing the oil's mobility leads to higher sweep efficiency and recovery efficiency.

Field studies of heavy oil reservoirs have been plentiful in the Literature. Saskoil et al. [9], presented a steam assisted gravity drainage study for a heavy oil reservoir in Canada, showing that oil may be produced economically from the reservoir. To remediate the challenge of steam coning, [9] argued that production wells should operate close to the pressure levels of the supporting aquifer. Tang et al. [10] presented a steam injection experimental study for extracting heavy oil in carbonate reservoirs, which typically encounter challenges because they are strongly naturally fractured and oil-wet. The authors were able to demonstrate that oil recovery from the carbonate reservoir is primarily dominated by imbibition, viscosity reduction, and in-situ steam generation within the core, where the latter is a promising aspect to increase recovery levels.

With the growing trend towards thermal methods for heavy oil recovery and the increasing availability of reservoir data, history matching of these reservoirs is necessary for determining reservoir formation properties and forecast reservoir production. Bao et al. [11] history matched the SAGD operation of the Liaohe Field in China in order to optimize the thermal injection process as well as the energy intensity of the injected steam. Hiebert et al. [12] presented a history matching study for determining the size, shape, and growth of the steam chamber in a SAGD project, showing that the incorporation of 4D seismic surveys assists in improving the categorization of the reservoir and the evolution of the steam chamber. The development of 4D seismic has led to increased interest in the integration of geophysical data into history matching and several studies on the integration of 4D time lapse seismic data attributes were conducted [13]–[16]. With the growing necessity to obtain a detailed understanding of the interwell regions in reservoirs, cross-well seismic tomography has been considered as a viable technique for overcoming the resolution limits of surface seismic techniques. Zhang et al. [17] utilized cross-well seismic tomography for monitoring the CO₂ injection process for the Ketzin field in Germany, and showed a clear seismic signal anomaly for the CO₂ injection process. For heavy oil reservoirs, cross-well seismic tomography was used for monitoring the reservoir architecture and steam chamber growth as shown in [18] for the Christina Lake heavy oil reservoir in Canada. The authors indicated that the reservoir heterogeneity may significantly influence the growth process of the steam chamber that was also detected via cross-well seismic data.

Heavy oil extraction has become of considerable interest in Saudi Arabia in the last decades, particularly for the Wafra oil field, which has drawn considerable investment for recovering heavy hydrocarbon components using steam drive [19]. Growing investment, enhanced formation understanding and tracking

the evolution of the steam chamber are key components to optimize field production strategies and reservoir recovery.

In this work, we present a cross-well seismic assisted reservoir history matching study of a steam drive heavy oil reservoir using an ensemble based history matching technique. The studied reservoir approximates a subpart of the Wafra oil field and the field development setup was organized to match the real field operations as close as possible. Utilizing cross-well seismic data, obtained from a full-waveform solver, that exhibit a strong signal contrast caused by the steam injection leads to a considerable enhancement in the matching of the observed well data and forecasting the well deliverability. The study outlines the feasibility and benefits of the integration of cross-well seismic data for reservoir history matching purposes and the applicability for developing optimized production strategies for enhancing reservoir characterization of the Wafra oil field.

II. METHODOLOGY

In this section, the thermal history matching framework integrating cross-well full-waveform seismic data is presented. We first briefly outline the reservoir simulator, then introduce the full-wave acoustic waveform solver followed by the history matching technique. A flowchart representation of the history matching setup is shown in Figure 1.

II.1. RESERVOIR SIMULATOR

For the reservoir model we used the thermal reservoir simulator E300 in Eclipse [20]. Thermal reservoir simulation assumes that the mass of each component, as well as the energy and the volume is preserved, leading to the following system of equations,

$$-\frac{d}{dt}(V_p m_{fl}) = F_{fl} + Q_{fl} \quad (1)$$

$$-\frac{d}{dt}(V_b e) = F_e + C_e + Q_{HL} + Q_e. \quad (2)$$

$$V_p = V_f \quad (3)$$

where V_p is the pore volume, V_b the bulk volume, m_{fl} the molar densities for either the hydrocarbon or water component, F_{fl} the net flow rate into neighboring grid blocks, Q_{fl} the net flow rate into the wells during the time step, e the bulk internal energy density, F_e the convective enthalpy flow rate into neighboring grid blocks, C_e the conductive energy flow rate into neighboring grid blocks, Q_{HL} the conductive energy flow rate to the surrounding rocks (heat loss), Q_e the net enthalpy flow rate into the

wells during the time step, and V_f the fluid volume. The subscript fl denotes either the N hydrocarbon components or water.

These equations are complemented by thermodynamic equilibrium conditions, flash equations for the change between the different components and heat conduction equations for relating the temperature change to changes in the component concentrations. For a more detailed description of the solution setup, the reader may refer to the technical description of Eclipse 300 solver [20]. The systems of equations are solved iteratively via a Newton-Raphson method.

II.2. SEISMIC SOLVER

Biot's theory [21], [22] deals with the propagation of acoustic waves in fluid-saturated porous solids and have been extensively applied for estimating acoustic wave velocities in fluid-saturated media [23]. The theory provides a framework for predicting the frequency-dependent velocities of saturated rocks in terms of dry-rock properties, which also enables the estimation of the reservoir compaction caused by the oil extraction [22]. The main assumptions of Biot's theory are that the underlying rocks are isotropic and that all minerals making up the rock structure have the same bulk and shear moduli [21]. While Gassmann's equations have been widely used due to its simplicity and correspond to the Biot-velocities in the low-frequency limit, for high-frequency seismic waves (as encountered for cross-well seismic imaging) Gassmann's equation underestimates velocities by around 10 % [24]. For the full acoustic wave propagation solvers, this may lead to distorted seismograms and hence misrepresentation of the formation structure. For the underlying reservoirs and cross-well seismic tomography applications, the high-frequency assumption of Biot is valid [25] and the P-wave velocity is represented as

$$V_{P\infty} = \sqrt{\frac{\Delta + \sqrt{\Delta^2 - 4(\rho_{11}\rho_{22} - \rho_{12}^2)(PR - Q^2)}}{2(\rho_{11}\rho_{22} - \rho_{12}^2)}}, \quad (4)$$

where Δ, P, R, Q and $\rho_{11}, \rho_{12}, \rho_{22}$ are parameters computed from the effective bulk K_r and shear moduli of the rock μ_r , the porosity ϕ , the density of the rock ρ and fluid ρ_{fl} and the tortuosity parameter α [22], [26]. The velocity and density profiles obtained from Biot's petrophysical transformation are then incorporated into the cross-well seismic tomography setup. For determining the dependence of the seismic wave propagation, we have solved the acoustic wave equation [27] as outlined in the appendix. The equations were discretized via a fourth-order finite difference formulation as presented in Levander et. al., [27]. The computed particle velocities were multiplied with the density at the recorded well [28], leading to the computation of the time lapse difference that was incorporated into the history matching process.

II.3. HISTORY MATCHING METHODS

For history matching the Ensemble Kalman Filter (EnKF) was implemented. The state-space formulation for the reservoir history matching problem is given by

$$x_{k+1} = M_k(x_k) + \eta_k, \quad (5)$$

$$y_k = h_k(x_k) + \epsilon_k, \quad (6)$$

where M_k represents the forward model (reservoir simulator) with the state vector x_k consisting of the static parameters, permeability and porosity, and dynamic variables, pressure and saturation, η_k is a Gaussian noise representing model errors and y_k the observation vector obtained via a nonlinear observation function h_k perturbed by a Gaussian random noise ϵ_k . The subindex k represents the k -th filtering step (when data are available), and the forward model maps the static parameters, permeability and porosity, to themselves. The observation operator encompasses both production data and time lapse seismic survey data. The time lapse seismic survey data are incorporated as changes of the seismic data in percent between successive surveys.

II.3.1. EnKF

The EnKF was first introduced by Evensen et al. [29], and has been ever since extensively applied in the field of reservoir history matching [30]. Being fundamentally based on the Kalman Filter (KF), the EnKF represents the distribution of the system state by a collection, or ensemble, of state vectors approximating the covariance matrix of the state estimate by the ensemble sample covariance. In the context of history matching, the state vectors consist of the permeability, porosity and water saturation fields that differ for each vector or ensemble member and variation between the different ensemble members shall represent the uncertainty of these properties. Despite the fact that the EnKF updates are based on only means and covariances (i.e., second order statistics neglecting higher order moments of the joint probability density distribution of the state variables) and that these covariances are computed from a finite size ensemble, the EnKF has shown to work remarkably and efficiently well for a variety of problems compared to optimization based deterministic history matching algorithms [30]. Seeking an efficient method, achieving good matching for a variety of different problems, the EnKF has naturally become one of the methods of choice for reservoir history matching.

In order to achieve efficient computation and to handle nonlinear observations, we have implemented an observation matrix-free implementation of the EnKF. Let N_e be the ensemble size and $X_k = [x_{1,k}, \dots, x_{N_e,k}]$ the state ensemble matrix at the k -th iteration step, with $x_{i,k}$ denoting the state vector of the i -th ensemble member at the k -th time step. The EnKF operates in two steps:

- A forecast step to integrate the ensemble forward in time with the reservoir simulator to compute the forecast ensemble $X_k^f = [x_{k,1}^f, \dots, x_{k,N_e}^f]$ from which the forecast mean and covariance are computed.
- An analysis step to update the forecasted ensembles with incoming data before proceeding to a new forecast cycle.

More explicitly, define the scaled covariance anomaly

$$A_k = X_k^f - \frac{1}{N_e} \left(\sum_{i=1}^{N_e} x_{i,k}^f \right) e_{1 \times N_e}, \quad (7)$$

with $e_{1 \times N_e}$ denoting the matrix with ones as elements and size $1 \times N_e$ and

$$[H_k]_{:,i} = h_k(x_{i,k}^f) - \frac{1}{N_e} \sum_{j=1}^{N_e} h_k(x_{j,k}^f) \quad (8)$$

the matrix observation matrix with $h_k(x_{i,k}^f)$ being the nonlinear observation for the i -th forecast ensemble state vector $x_{i,k}^f$. Then for the data matrix D_k , with the columns containing the observation perturbed with noise sampled from the observational error covariance matrix R_k , the EnKF update step can be written as [31]:

$$X_k^a = X_k^f + \frac{1}{N_e - 1} A_k H_k^T \left(\frac{1}{N_e - 1} H_k H_k^T + R_k \right)^{-1} (D_k - h_k(X_k^f)), \quad (9)$$

The EnKF therefore updates each ensemble independently in such a way that the resulting sample mean and covariance of the updated ensemble exactly matches the Kalman filter analysis and associated error covariance [31]. For further details about the EnKF, the reader may refer to the review articles of Aanonsen et. al. [30] and Luo et al. [32].

III. NUMERICAL EXPERIMENTS AND RESULTS

In this section, we present the experimental setup followed by a study of the performance in matching various production parameter and characterizing accurately that is subsequently concluded by a history matching results analysis.

III.1. EXPERIMENTAL SETUP

The studied reservoir represents a synthetic representation of a part of the Wafra field at the border between Saudi Arabia and Kuwait. The reservoir consists of a carbonate rock formation located at a depth of 1,650

meters (top of the reservoir) extending to around 2,800 meters [19], [33]. The reservoir is around 10,000 meters in length, and around 11,000 meters in width, and is separated by four communicating fault lines. Grid size resolution is about 230 meters in the horizontal plane, and 150 meters in the vertical direction, resulting in a $36 \times 37 \times 8$ grid. The grid size was chosen such as to enable efficient simulation and achieve sufficient resolution at the reservoir scale to capture the main dynamics in the reservoir. The reference permeability and porosity fields were obtained using unconditional simulation using Petrel based on an exponential variogram model with anisotropy axis of 3256 meters in the x-direction, 3950 meters in the y-direction, and 29.6 meters in the vertical direction. For the unconditional simulation of the reference permeability a log-normal distribution with mean 800 mD and standard deviation 500 mD, and for the reference porosity a normal distribution with mean 35 percent and standard deviation of 7 percent was assumed. Sampling the reference permeability and porosity fields at all wells, an initial ensemble of permeability and porosity fields were obtained using conditional simulation with the permeability ranging between 50 mD and 13,000 mD and the porosities between 25 and 49 percent. The mean and the standard deviation for the log-normal and normal distribution for the conditional simulation are estimated from the well logs and were 755 mD (mean) and 490 mD (standard deviation) for the permeability fields, and 34.2 percent (mean) and 6.6 percent (standard deviation) for the porosity fields. For a more detailed description about the Petrel process the reader may refer to the Petrel handbook and reference guide [34]. The reference permeability and porosity fields are presented in Figure 2. The permeability tensor was assumed to be diagonal with $K_{zz} = K_{yy} / 5 = K_{xx} / 5$.

The well pattern for the domain is outlined in Figure 3 and consists of 10 producer wells, and 9 Injector wells. The reservoir initial pressure reached 280 bar and the producing wells were pressure controlled at 120 bar. The injectors assume pressure levels of 300 bar. The steam quality at the injectors is 80 %, which is consistent with rates achieved at the Wafra field [33], [35]. The components heavy oil, methane and water were explicitly modeled in the thermal simulation, with the heavy oil initially assumed undersaturated. The relative permeability curves for the oil and water phases as well as the gas and oil phases with the presence of connate water are shown in Figure 4. Starting from 2008 the field was then history matched in 2010 and 2013 and forecasted until 2018 to retrieve estimates for production, oil recovery and water saturation levels. Cross-well seismic surveys were conducted in 2008, 2010 and 2013 and were transformed into a seismic pseudo – impedance (product of formation density and particle velocity obtained from the full waveform solver). Measurement observation error for the seismic impedance was set to 10 % of the observed signal. The realistic 3D reservoir is then employed in a history matching experiment to forecast different production parameters, in addition of providing estimates for the pressure, water, oil and gas saturation levels, while incorporating both production and seismic cross-well

data. The seismic cross-well data were obtained using a full-waveform solver as outlined above computing time lapse response of the pseudo seismic impedance (the product of formation density and particle velocity). For the production observations the bottom hole pressure (BHP) for all producer wells and the total field production per day were matched. For the BHP observation error rate of 20 psi was assumed and the field production error rate is around 3 %, based on the specified target rate. The ensemble size is set to 60 members, which allowed maintaining matching quality at reasonable computational cost. Computational time for a full history matching was around 5 hours and 40 minutes on Dell workstation. In the forthcoming study, BASE denotes the history matching experiment in which only production data are history matched and SEHM for the case where the seismic data are history matched. Matching improvements were evaluated by comparing the Root-mean squared errors

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (d_i^{ref} - d_i^{est})^2}{N}}, \quad (10)$$

for the different experiments, where d_i^{ref} is the i-th component of the considered observation data, and d_i^{est} is its corresponding estimate obtained from the mean estimate.

III.2. RESERVOIR CHARACTERIZATION USING SEISMIC DATA

The following sections will analyze the history matching performance for a steam drive heavy oil reservoir integrating full-waveform cross-well seismic data. We will first evaluate the history matches for individual critical reservoir parameters, followed by an analysis of the quality of the reservoir characterization, and finally conclude with summary of the history matching performance.

III.2.1. History Matching Performance

We first outline in Figure 7 the oil saturation levels for different times during the history matching study. The injection of steam causes a sharp drop in the heavy oil levels, especially in the uppermost layers, leading to steam migrating to the top and heavy oil to the producer wells. The simulation results demonstrate well the gravity drainage effects caused by steam injection, where the hot steam that is injected into the reservoir moves to the top of the reservoir, while the higher density oil components migrate downwards and to the wells. This in particular leads to significantly lower oil saturation in the upper reservoir layers as compared to deeper layers in year 2013, showing the segregation effect. In order to investigate the recovery efficiency from the reservoir, we present in Figure 8 and Figure 9 the well oil production rates for producer wells P10 and P03. Well oil production shows elevated levels of heavy oil production for the first three years, followed by a considerable drop in the oil production rates caused by increased water production, both in liquid as well as gaseous form, as shown in Figure 10 for the field

water cut. Steam breakthrough at the producer wells is further well visible in the well volume production rates for producer P06 as shown in Figure 11. While initially the injection of steam causes liquid hydrocarbons to migrate to the producer wells and being produced, continuing steam injection gradually reduces the efficiency of increasing the mobility of the heavy oil, and as the reservoir depletes more and more water migrates towards the producers. Similar to the oil production, wet gas production decreases substantially after the third year, outlining increased depletion of the reservoir. Contrasting the history matches and the ensemble development having led to enhanced history matches when using cross-well seismic data, the figures outline the improvements in history matching and benefits from the integration of cross-well seismic data for the considered reservoir.

Having compared the history matches for the individual well observations such as well volume production, we will focus our attention on the characterization of the reservoir formation that is essential for carbonate reservoirs like Wafra. We present in Figure 13 and Figure 14 a comparison of the porosity and permeability estimates for the BASE and SEHM cases. The estimates are obtained via computing the mean over all ensemble members of the corresponding cases. While the BASE experiment is strongly affected by the smoothening characteristic of the EnKF, the incorporation of seismic data avoids this challenge and is able to estimate adequately the low and high parameter value regions, especially for the permeability field. This is exemplified in Figure 15, which compares the permeability and porosity estimates of SEHM to the initial and BASE estimate. The scatter plots outline the smoothening characteristic caused by the Gaussian assumption that leads to a rather homogeneous permeability and porosity estimate when only production data are assimilated. When cross-well seismic data are integrated, the averaging effect is remediated and the heterogeneity is better estimated, as outlined by the increase in the slope of the SEHM cloud. The conclusions drawn from the above figures are confirmed by the RMSE values for the porosity and permeability field as shown in Figure 16. The improved characterization of the reservoir's permeability and porosity in SEHM is exemplified in the considerable reduction of the RMSE in both cases as compared to the BASE case. In quantitative terms, the improvement is around 20 % for both fields with the permeability field exhibiting a stronger reduction as compared to the porosity field.

We further analyze in Figure 17 the water vapor saturation differences of the estimates with respect to the reference field on 1.1.2010 and 1.1.2013. A comparison between the estimates outlines the improved tracking of the steam front when incorporating cross-well seismic data. Specifically, the faster advancing steam front in the center in 2010 and at the southern flank of the reservoir in 2013 is well captured in SEHM as compared to the BASE, where the water vapor saturation levels, in particular in the uppermost reservoir layers, are lower by around 20 percentage points. The enhanced vapor front tracking correlates well with the permeability estimation improvements, as outlined in Figure 13. The higher permeability

areas in the south of the reservoir, which are clearly detected when using SEHM as compared to the BASE instance, are well reflected in the higher steam saturation levels.

We further analyze the impact of different seismic noise levels on the history matching and outline its effects in Figure 18. A comparison between the figures outlines that lower level of noise lead to better history matches and forecasts and that the integration of seismic data is still fairly robust for noise levels up to 30 %. For noise levels above the history matches significantly deteriorate and lead to a considerable overestimation of the total oil production levels in producer 11. The main reason for the deterioration in the history matching results is that for noise level of more than 30 % the time lapse seismic data contrast is rather weak or of opposite direction and hence the update step may lead to poorer estimates and consequently worse history matches.

The conclusion that can be drawn from the analysis is that while higher noise levels lead to a deterioration of the matching quality, the framework still delivers good qualitative history matches for noise levels improving by more than 30 %.

III.2.2. History Matching Summary

We have summarized in Table 1 the matching improvement results for a selected number of well observations (well volume production, etc.) for the additional incorporation of the cross-well seismic data compared to when only production data are history matched. A more comprehensive analysis of the matching enhancements of all well observations is presented in Figure 19. The history matching enhancement was computed as

$$MI = \frac{RMSE_{BASE} - RMSE_{SE}}{RMSE_{BASE}}. \quad (11)$$

where $RMSE_{BASE}$ is the root-mean squared error (RMSE) of the case when only production data are history matched, and $RMSE_{SE}$ the RMSE when cross-well seismic data are additionally integrated into the history matching.

Analyzing the data outlines the considerable reductions in the RMSE for the field and well parameters, outlining the tighter matching that was achieved. Matching improvements are particularly significant for the water cut, water in place and oil production levels, demonstrating the benefits of the integration of seismic data for tracking the steam and water fronts within the reservoir. The matching improvement rates are summarized in Figure 19 showing for the majority of well observations matching improvements rates from 5 to 40 %, with a few parameters moving beyond 50 %. Around 111 different well observations matching improvement rates were computed and the histogram represents its distribution.

IV. DISCUSSION AND CONCLUSIONS

Rapid depletion of the world's major oil reservoirs has encouraged investment into unconventional oil reservoirs amongst others the recovery of heavy oil via the injection of steam. While conventional reservoirs are the main oil source in the Arabian Peninsula, heavy oil fields in carbonate formations, such as Wafra, have been brought on production to be able to maintain reservoir production levels at the existing levels. For improving reservoir characterization and history matching of steam drive heavy oil reservoirs, we have presented an ensemble Kalman filter based history matching study integrating full-waveform seismic data and examined its performance on a synthetic representation of the Wafra oil field. Cross-well seismic data have been successful in monitoring the propagation of the injected steam within the reservoir and may be further used in improving history matching and forecasting of these fields. The full-waveform seismic data were directly integrated into the history matching process using a full-waveform seismic solver, and the results indicated a considerable improvement in the history matches for several production well data, being in the range of 5 to 40 %. Furthermore, it was demonstrated that the reservoir was better characterized with permeability estimates being close to the reference permeability field, and the RMSE for both the porosity and permeability field is significantly reduced. Furthermore, the water saturation within the reservoir was further fairly well captured when integrating cross-well seismic data. The history matches were still fairly robust even for noise levels in the cross-well seismic data of up to 30 %, while for larger noise levels the seismic signal contrast may be rather weak and hence may lead to a deterioration in the history matching results. The EnKF has shown to perform reasonably well for history matching heavy oil reservoirs and capturing the nonlinear dynamics caused by the steam injection, however a more extensive investigation for several other heavy oil fields may be necessary. Concluding, the framework presents an efficient approach for the history matching of steam drive heavy oil reservoirs and the integration of full-waveform cross-well seismic data for enhancing history matching. Further research may investigate the performance of the EnKF and the integration of cross-well seismic data for several other fields, as well as discuss approaches to minimize the impact of higher noise levels on the history matching quality.

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<i>Matching enhancement (%)</i>	
Parameter	SEHM
Field Average Pressure (FPR)	19.62
Field Oil Production Rate (FOPR)	16.72
Field Water Cut (FWCT)	5.87
Field Water In Place (FWIP)	51.79
Well Oil Production Rate (WOPR, P06)	18.83
Well Oil Production Rate (WOPR, P09)	11.11
Well Volume Production Rate (WVPR, P02)	13.77
Total Well Volume Production (WVPT, P10)	8.92
Well Productivity Index (WPI, I08)	14.72
Total Well Oil Production (WOPT, P06)	37.36
Total Well Oil Production (WOPT, P09)	30.07
Well Water Injection Total (WWIT, I08)	25.47
Well Water Cut (WWCT, P09)	39.44
Well Wet Gas Production Rate (WWGPR, P06)	18.83

Table 1: Matching improvements for SEHM compared to the BASE case as outlined in equation (11). An analysis of the data outlines the considerably better history matches and lower RMSE when incorporating cross-well seismic data as compared to the BASE case.

Figure 1: Flowchart representation of the seismic assisted History Matching framework.

Figure 2: Reference porosity and permeability fields of the formation.

Figure 3: Well pattern for the injector and producer wells.

Figure 4: Relative permeability curves for oil versus water and gas versus oil when only connate water is present.

Figure 6: Flowchart of the experimental study.

Figure 7: Oil saturation levels for the reference porosities and permeabilities for different times.

Figure 8: Well Oil Production for producer P10 (WOPR; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching).

Figure 9: Well Oil Production for producer P03 (WOPR; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching).

Figure 10: Field Water Cut (FWCT; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching).

Figure 11: Well Volume Production for producer P06 (WVPR; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching).

Figure 12: Wet Gas Production Rate for producer P02 (WWGPR; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching).

Figure 13: Final permeability estimates as they result from the history matching experiment incorporating only production data (BASE) and production and seismic data (SEHM) compared to the reference permeability.

Figure 14: Final porosity estimates as they result from the history matching experiment incorporating only production data (BASE) and production and seismic data (SEHM) compared to the reference porosity.

Figure 15: Scatter plot comparison between the reference field and the initial, BASE and SEHM field estimates.

Figure 16: RMSE comparison between the BASE and SEHM.

Figure 17: Water saturation differences between the estimated and reference field in 2010 and 2013. The left panels indicate the estimates for SEHM and the right panels for the BASE case.

Figure 18: Total well oil production of producer P11 for different levels of noise in the seismic signals (WOPT; red line – reference level, gray – ensemble levels, blue – ensemble mean estimate, magenta – end of history matching). The history matches are still robust for noise levels up to around 30 %, however deteriorate significantly for levels above.

Figure 19: Histogram representation of matching improvements of SEHM with respect to the BASE case.

Highlights

- Performance of steam injection for the recovery of heavy oil for a synthetic Wafra formation
- Reduction in the uncertainty for the history matches using time lapse seismic data
- Enhanced characterization of the reservoir formation, in particular the permeability and porosity fields
- Steam front tracking