IPTC-17725-MS

A Novel 3D Viscoelastic Acoustic Wave Equation Based Update Method for Reservoir History Matching

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This paper was prepared for presentation at the International Petroleum Technology Conference held in Kuala Lumpur, Malaysia, 10–12 December 2014.

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Abstract

The oil and gas industry has been revolutionized within the last decade, with horizontal drilling and hydraulic fracturing enabling the extraction of huge amounts of shale gas in areas previously considered impossible and the recovering of hydrocarbons in harsh environments like the arctic or in previously unimaginable depths like the off-shore exploration in the South China sea and Gulf of Mexico. With the development of 4D seismic, engineers and scientists have been enabled to map the evolution of fluid fronts within the reservoir and determine the displacement caused by the injected fluids. This in turn has led to enhanced production strategies, cost reduction and increased profits. Conventional approaches to incorporate seismic data into the history matching process have been to invert these data for constraints that are subsequently employed in the history matching process. This approach makes the incorporation computationally expensive and requires a lot of manual processing for obtaining the correct interpretation due to the potential artifacts that are generated by the generally ill-conditioned inversion problems. I have presented here a novel approach via including the time-lapse cross-well seismic survey data directly into the history matching process. The generated time-lapse seismic data are obtained from the full wave 3D viscoelastic acoustic wave equation. Furthermore an extensive analysis has been performed showing the robustness of the method and enhanced forecastability of the critical reservoir parameters, reducing uncertainties and exhibiting the benefits of a full wave 3D seismic approach. Finally, the improved performance has been statistically confirmed. The improvements illustrate the significant improvements in forecasting that are obtained via readily available seismic data without the need for inversion. This further optimizes oil production in addition to increasing return-on-investment on oil & gas field development projects, especially in offshore environments.

INTRODUCTION

Reservoir history matching incorporating time lapse seismic data has gained growing interest in the reservoir engineering community to complement the spatially sparse well information by global seismic data to enhance production forecast and improve the characterization of the reservoir. Well production data are key data specifying the quality of a history match and are the main source of information used

for history matching. With the advances in seismic techniques and the enhancements in data processing, reservoir monitoring using time lapse seismic data has become increasingly feasible for a variety of reservoirs. Extensive work has been conducted in better detecting the time lapse changes in the reservoir using seismic techniques^{1–4} and has provided a more detailed understanding of the dynamics in the reservoir as compared to solely using production data. Time lapse seismic data have increasingly been utilized for complementing production data in reservoir history matching, having shown to yield significantly better subsurface parameter estimates and history matches^{5–8}. Amongst others, Skjervheim et. al.⁷ has been amongst the first to integrate time lapse seismic data for history matching applications using the ensemble Kalman filter. The work outlined the enhanced trackability of the propagating water fronts within the reservoir and corresponding refined estimates for reservoir permeability and porosity. In a more recent article, Leeuwenburgh et. al.⁹ avoided the usage of seismic data attributes via directly integrating time lapse seismic response data obtained from a convolutional model approach. The direct incorporation of the time lapse seismic data, avoiding the inversion of these data for data attributes, proves beneficial in accurately characterizing the time lapse response anomaly caused by the injection of water. While surface seismic techniques have exhibited good response in detecting mass redistributions within the reservoir, limited seismic resolution and fluid discrimination is still posing a challenge. In order to overcome the limited resolution in particular for interwell regions, cross-well seismic techniques (Figure 1) have been explored for increasing resolution in the interwell regions and hence better characterizing the fluid displacement¹⁰. Cross-well seismic surveys were conducted rather frequently in recent years for investigating fluid saturation levels and obtain a more comprehensive understanding of the formation for planning and executing secondary and tertiary recovery mechanisms. While the incorporation of cross-well seismic data attributes can deliver considerable improvements in the quality of history matches, the separate inversion of the seismic data for obtaining these attributes may incorporate an undesirable bias in the inverted model. Additionally, ray tracing approaches using a convolutional model are not applicable for cross-well applications necessitating a full-wave approach for modeling the propagation of the seismic waves within the reservoir formation.

With the growing availability of time-lapse seismic data for reservoir monitoring purposes, linking these data directly to the dynamics in the reservoir has encountered increasing interest, in particular in history matching^{11–14}.

Reservoir history matching has experienced considerable changes in the last decade with data assimilation techniques attracting substantial interest in coping efficiently with the increasing number of parameters that are history matched and the request to quantify efficiently the uncertainty levels in the estimated parameters. Ensemble Kalman filtering (EnKF) techniques have particularly encountered growing use due to their ability to efficiently estimate hundred of thousands parameters, cope efficiently with strongly nonlinear models and their simultaneous quantification of the uncertainty. Originally put forward by Evensen et. al.¹⁵ the EnKF approximates the covariance of the ensemble states by a low-rank approximation obtained from an ensemble using a monte carlo approach. For history matching applications this reduces the covariance matrix from a square matrix with row and column sizes in the hundred of thousands, to one whose column size is reduced to the order of hundred. This favorable characteristic has led to the EnKF being applied for a variety of history matching applications^{11,16} as outlined below.

Figure 1—Cross-well Seismic Tomography illustrating the good differentiation between rock and fluids.

In this article I present a full wavefield seismic wave propagation based reservoir history matching framework that consists of full wavefield seismic wave propagation solvers interfaced to a data assimilation framework incorporating the EnKF. The full wavefield seismic wave propagation solvers enable to deal with strongly heterogeneous cross-section between the wells, and accurately models the propagation of seismic waves within the cross-well formation. History matching results exhibit the positive effects the incorporation of full waveform retrieved seismic data have on reducing formation uncertainty and improving history matching results.

METHODOLOGY

The history matching framework incorporating 3D full wave seismic data is outlined in Figure 2. The framework performs sequential history matching incorporating at each EnKF update step besides well data full wave cross-well seismic data obtained from cross-well seismic surveys. In the following, the EnKF data assimilation is introduced followed by outlining the petrophysical transformation and the section is concluded by discussing the full waveform seismic solver.

DATA ASSIMILATION

The state space formulation for the subsurface parameter and state estimation is given by the system

$$z_k = \mathcal{M}(z_{k-1}, \theta_{k-1}) + \eta_k \quad (1)$$

$$y_k = h(z_k, c_k) + \epsilon_k \quad (2)$$

where z_k represents the dynamic parameters at the k -th update step, c_k the static parameters at the k -th update step, where $\theta_{k-1} = \theta_k$, y the observation and η and ϵ are the zero mean white noises whose covariance matrices are given by B and R . The reservoir simulator is represented by M and the function h maps the static and dynamic parameter vector into the observation space. The history matching framework incorporates the EnKF that was first introduced by Evensen et. al. 17. The EnKF is a sequential data assimilation algorithm that represents the distribution of the system state via a collection of state vectors approximating the covariance matrix of the state estimate by a sample covariance matrix. The EnKF update steps have shown to efficiently perform history matches with good quality despite the fact that the updates are solely based on a second order statistics, taking into account only mean and covariances of the model variables ^{11,16}.

The implementation of the EnKF was as follows. Given N_e 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 $x_{i,k} = [z_{i,k}, c_{i,k}]$ denoting the state vector of the i -th ensemble member at the k -th time step. The state vector consists of the dynamic variables $z_{i,k}$ such as water saturation and pressure levels, and the static variable $c_{i,k}$, encompassing permeability and porosity. The EnKF then first integrates the ensembles forward in time to compute the sample mean and covariance and then updates the forecasted ensembles within the incoming data in the analysis step that are used in the next forecast step. The update step is then written as

$$X_k^a = X_k^f + \frac{1}{N_e - 1} A_k H_k^T \left(\frac{1}{N_e - 1} H_k H_k^T + R_k \right)^{-1} (D_k - h_k(X_k^f)) \quad (3)$$

Figure 2—History Matching Framework for the incorporation of time lapse seismic data.

where $A_k = X_k - \frac{1}{N_e} \left(\sum_{i=1}^{N_e} x_{i,k} \right) e_{1 \times N_e}$ is the scaled covariance anomaly with $e_{1 \times N_e}$ denoting the matrix with ones as elements and size $1 \times N_e$. Furthermore, $[H_k]_{:,i} = h_k(x_{i,k}) - \frac{1}{N_e} \sum_{j=1}^{N_e} h_k(x_{j,k})$ is the the matrix observation anomaly with $h_k(x_{i,k})$ being the nonlinear observation for the i-th ensemble state vector $x_{i,k}$ and D_k , the data matrix with the columns containing the observation perturbed with noise sampled from the observational error covariance matrix R_k . total runtime for the considered test cases were around 15-20 minutes.

PETROPHYSICAL TRANSFORMATION - BIOT'S THEORY

Biot's theory^{18,19} deals with the propagation of acoustic waves in fluid-saturated porous solids and have been extensively applied in estimating acoustic wave velocities in fluid-saturated media²⁰. The theory provides a framework for predicting the frequency-dependent velocities of saturated rock in terms of dry-rock properties that enables also to estimate the reservoir compaction caused by the oil extraction via Biot's poroelasticity theory¹⁹. 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 moduli¹⁸. 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 %²¹. This may for the full acoustic wave propagation solvers lead to significantly distorted seismograms and hence leads to a misrepresentation of the formation structure. For the underlying reservoirs and cross-well seismic tomography applications, the high-frequency assumption is valid and the P-wave is represented by^{19,23}

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

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_f and the tortuosity parameter α .

SEISMIC SOLVER

The velocity profiles and density profiles obtained from the petrophysical transformation module are then incorporated into the cross-well seismic tomography setup. For determining the dependence of seismic wave propagation, I have solved the viscoelastic wave equation 24 given in its general form in 3D by

$$\rho \frac{\partial u_x}{\partial t} = \frac{\partial \sigma_{xx}}{\partial x} \quad (5)$$

$$\rho \frac{\partial u_y}{\partial t} = \frac{\partial \sigma_{yy}}{\partial y} \quad (6)$$

$$\rho \frac{\partial u_z}{\partial t} = \frac{\partial \sigma_{zz}}{\partial z} \quad (7)$$

and

$$\frac{\partial \sigma_{xx}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) - 2\mu \frac{\tau^s}{\tau_\sigma} \left(\frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) + \eta_{xx} \quad (8)$$

$$\frac{\partial \sigma_{yy}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) - 2\mu \frac{\tau^s}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_z}{\partial z} \right) + \eta_{yy} \quad (9)$$

$$\frac{\partial \sigma_{zz}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) - 2\mu \frac{\tau^s}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} \right) + \eta_{zz} \quad (10)$$

Figure 3—Initial porosity and permeability fields of the formation.

$$\frac{\partial \sigma_{xy}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) + \eta_{xy} \quad (11)$$

$$\frac{\partial \sigma_{yz}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) + \eta_{yz} \quad (12)$$

$$\frac{\partial \sigma_{xz}}{\partial t} = \pi \frac{\tau^p}{\tau_\sigma} \left(\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} \right) + \eta_{xz} \quad (13)$$

with $u = (u_x, u_y, u_z)$ being the velocity vector, σ_{ij} representing the components of the stress tensor that is assumed to be symmetric, and η_{ij} the memory variables that describe the anelastic characteristics of the dilatational wave, as described in Carcione²⁵. Furthermore, τ^p , τ^s denote the strain relaxation times for the p and s wave, and τ_σ the stress relaxation time.

Finally, λ and μ are the Lamé parameters²⁶. The equations were discretized via a fourth-order finite difference formulation as presented in Levander et. al.,²⁴. The computed velocities and stress fields are then transformed into impedance¹, leading to the computation of the time lapse difference that are incorporated into the history matching framework.

EXPERIMENTS

In the coming section, I am going to outline the experimental setup, and present an extensive analysis of the impact of seismic surveys on reservoir history matching and forecasting for a synthetic 3D reservoir.

EXPERIMENTAL SETUP

The studied reservoir is 1.25 km in length, in both x and y-direction and 100 m in the z direction, representing a cenozoic sedimentary rock reservoir structure that is found in the Arabian peninsula²⁸. The reservoir rock is assumed to consist of sandstones with the reference porosity and permeability field being obtained from unconditional simulations using an exponential variogram model with anisotropy axis of 320 m in the x-direction, 240 in y-direction and 25 in z-direction. Five samples each from the porosity and permeability were collected to determine the parameters of the variogram models for the ensemble permeabilities and porosities. 70 ensembles were generated via unconditional simulation for both permeability and porosity (based on the typically encountered ranges between 60 and 80, and the conclusion presented in²⁹) with the permeability tensor being assumed diagonal and $K_{33} = K_{11}/10 = K_{22}/10$. The ensemble permeability values range from 156 to 915 milli darcy with the porosity values between 8 % and 35 % (see Figure 3). The well pattern I considered is a five-spot pattern (as indicated in Figure 3) that is commonly employed in the oil exploration³⁰, meaning one injector in the center and four producers at the corners. The initial pressure levels within the reservoir were set at 5120 psi, ensuring

Table 1—Parameters of the three test cases considered for the analysis.

Case	<i>Test case parameters</i>		
	Total Sim. Time (years)	HM Time (years)	Update Time (years)
1	30	9	4
2	32	9	6
3	35	9	5
4	28	10	4
5	40	10	5

during the simulations that the producing wells maintain a pressure level of 4228 psi. The initial porosity and permeability fields are represented in [Figure 3](#).

The above described realistic 3D reservoir test case is then employed in a series of history-matching experiments that were employed for forecasting production and pressure levels and the reservoirs' evolution, incorporating production and Seismic measurements obtained from 3D simulations. For each state 2,500 parameters were estimated leading to a size of the state vector of 10,000. The total number of observations was between 700 and 1,000. Bottom hole pressure (BHP), water cut ratio (WCR) and production flux were measured at all wells, with standard measurement errors of 120 psi for BHP, and around 8 % measurement error rates for the other production data. For seismic measurements I have assumed error rates of around 10 %. These error rates are in agreement with the error rates encountered for real field productions ³¹.

For the analysis, I have studied five different test cases, as presented in [Table 1](#) that differ in their update and forecasting period. The overall simulation consists of the history matching period that is 9-10 years for all experiments that are followed by 21 to 30 years of forecasting with an update step being performed every 4 to 6 years.

In the section below, I first discuss on a series of examples the impact the additional seismic surveys have on various reservoir parameters, outline the production improvements and conclude the analysis by a quantitative comparison of the matching enhancements.

HISTORY MATCHING

I present in the section below an outline of the data obtained from cross-well seismic imaging and conclude by an analysis of the history matching quality incorporating seismic data.

CROSS-WELL SEISMIC IMAGING

In order to analyze the impact of the seismic seismograms and the change in the structure of the seismograms caused by reservoir changes, I present in [Figure 4](#) the seismograms with the 3D full wave acoustic wave equation recorded for the Biot model. The density and velocity profile indicate a low velocity and low density area around the source that unevenly spreads in the y direction when moving along the x axis. In particular, a high velocity zone crystallizes out for larger y values while for lower y values the velocity is almost comparable to that found at the source. These changes are clearly reflected in the seismogram recordings with the first receiver detecting the source acoustic wave first due to the higher velocity regions when considering a line between the source and receiver. This is despite the fact that the distance between the source and receiver 1 is around 100 m longer than that of the source to receiver 2. Additionally the long time lag in the first recording experienced at receiver 3 exhibits the low velocity profile structure leading to a consistent reduction in propagation velocity. The influence of density differences are also evidently featured in the seismogram. Pressure levels are approximately linearly related to density levels, implying increased pressure for increasing density. The stronger attenuation experienced at receiver 3 as compared to receiver 1 reveals this relationship in addition to the strong, almost exponential fall-off at receiver 2. Summarizing, the formation characteristics are clearly

Figure 4—Velocity and Density profile for Biot's model (left) and the seismogram recordings from three receivers. The receiver locations are indicated with black and the source in white. The receivers are denoted from 1 to 3, with 1 being above 1500 m, and 3 below 500 m

Figure 5—Oil production rates for the four producer wells comparing the incorporation of seismic data and its effect on forecasting production for case 1 using EnKF. (The red line represents the real production curve and blue being the mean of the ensemble curves indicated in gray)

observable in the seismogram recordings providing through direct incorporation into the EnKF substantial information for improved matching.

PRODUCTION ANALYSIS

Figure 5 represents a comparison of the oil production rates for the four producer wells incorporating the different seismic surveys. Comparing the differences in the production wells, one detects that the ensembles underestimate the production rates as compared to the real production curve implying that the field may be earlier decommissioned than necessary, leading to a substantial loss in cumulative production and hence lost revenue. While the underestimation may be severe for history matching only production data, the incorporation of seismic data into the history matching process aligns the individual ensembles closer to the real production output. This is deducible from the ability to more accurately determine reservoir parameters such as saturation between the wells and hence forecast more accurately the fluid displacement and consequently production levels for the reservoir. In quantitative terms, this is displayed with the incorporation of 3D cross-well seismic showing a matching enhancement of 65.16 %.

The improvement in matching can be even more profoundly seen in the cumulative oil production from the reservoir as exhibited in Figure 6. Performing conventional history matching incorporating production data from the wells exhibits a strong decrease in cumulative output as compared to the real reservoir

Figure 6—Cumulative oil production for the reservoir comparing the incorporation of seismic data and the production forecast for case 1 using EnKF. (The red line represents the real production curve and blue being the mean of the ensemble curves indicated in gray)

Figure 7—Water cut rates for the four producer wells for case 1 using EnKF. For the petrophysical transformation the Biot¹⁹ model was assumed. (The red line represents the real production curve and blue being the mean of the ensemble curves)

output leading to an underestimation of total output of around 4000 sm^3 . Incorporating seismic data into the matching and forecasting process subsequently decreases ensemble spread and raises the production forecasts, reducing the gap down to 1800 sm^3 for incorporating seismic data. In terms of RMSE errors, this has resulted in a matching improvement of 84.63 %. As discussed previously, seismic imaging enables the more accurate determination of fluid fronts within the reservoir and to measure its propagation speed throughout the reservoir. Incorporating cross-well seismic data results in a more global knowledge of the reservoir properties as compared to the rather localized information provided by production data. This in turn reduces uncertainty between the different ensemble members and leads to better prediction.

Besides production rates, water cut levels have been key factors for determining changes in production strategies, adapt injection levels and estimate the displacement of hydrocarbons. High water cut ratios are undesirable for several reasons such as the that for each injected amount of water only a marginal fraction of the outcoming fluid are hydrocarbons, the necessity to treat and dispose the produced water which can be especially in offshore locations a limiting factor both in terms of capacity as well as cost. In order to analyze the impact of the seismic surveys have on the water cut ratios, I present in Figure 7 a comparison of the water cut ratios for the producing wells. The ability to reduce ensemble spread via the exploitation of seismic data are clearly demonstrated also in the water cut ratios with matching being much tighter as

Table 2—Average matching improvements (in %) for the different production parameters and 5 test cases for the EnKF

Average Matching Enhancement (w.r.t. Prod. Data only)	
Parameter	Seismic EnKF
Test Case 1	
Oil prod. (Avg Wells)	38.11
Water cut (Avg. Wells)	40.08
Pressure level	35.01
Total oil prod.	51.53
Total water cut	48.76
Test Case 2	
Oil prod. (Avg Wells)	60.80
Water cut (Avg. Wells)	68.66
Pressure level	65.44
Total oil prod.	81.63
Total water cut	74.12
Test Case 3	
Oil prod. (Avg Wells)	61.43
Water cut (Avg. Wells)	69.42
Pressure level	63.07
Total oil prod.	81.83
Total water cut	73.21
Test Case 4	
Oil prod. (Avg Wells)	63.76
Water cut (Avg. Wells)	70.51
Pressure level	56.75
Total oil prod.	84.20
Total water cut	78.00
Test Case 5	
Oil prod. (Avg Wells)	57.62
Water cut (Avg. Wells)	69.19
Pressure level	59.13
Total oil prod.	81.97
Total water cut	70.57

compared to sole production data matching. The prime reason for the improvements follow from the fact that large deviations can be significantly reduced as clearly observable due to the incorporation of the state of the formation and hence improve accuracy of the prediction of additional amounts of water that may flow to the producing wells. Quantitatively this is reflected in matching improvements of 70.02 %.

COMPARISON

I have summarized in the matching results for the different test cases and seismic surveys incorporating the Biot velocity model. The results uniformly indicate a matching improvement in the forecasting production results. This loss in information causes then e.g., in the case of the production (see [Figure 5](#)) to significantly underestimate the potential production output via estimating that the hydrocarbon reservoir size is less than in reality.

DISCUSSION AND CONCLUSIONS

Although prevalent for decades, seismic techniques have acquired in the last decade tremendous amount of importance with the introduction of 4D seismic imaging and reduction of cost of seismic surveys, making it economically feasible to employ these techniques for a more accurate image of the subsurface and hence increase success rates in stimulating production as well as forecasting the evolution of existing

reservoir structures. Especially in offshore field developments knowing the exact location of the reservoirs hydrocarbons is of paramount importance to avoid excessive costs and hence increasing profitability. I have presented a thorough analysis of the impact of seismic cross-well data on reservoir history matching and forecasting, showing a significant decrease in ensemble uncertainty and improved reservoir forecasting. The ensemble-based history matching scheme incorporates seismic data that are obtained from full wave propagation solvers. The simulation results demonstrate significant improvement in matching of reservoir formation parameters. The method offers some important insights into utilizing seismic data for reservoir history matching such as

- full wave field modeling enables a more detailed investigation of the reservoir properties incorporating both density and velocity profile directly as compared to a single reflectivity function
- including seismic data enhances the sensitivity of changes in the reservoir structure

Overall, incorporating seismic information into reservoir history matching has shown to reduce ensemble uncertainty, provide better forecasts and for the considered structure the direct incorporation of seismic data is feasible to considerably improve the history matching. Future work is intended to examine the method on more complex reservoir structures.

Acknowledgement

Research reported in this publication was supported by King Abdullah University of Science and Technology (KAUST).

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