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A Time Domain Update Method for Reservoir History Matching of Electromagnetic Data

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Abstract

Technology has fundamentally changed the oil and gas industry enabling it to extract substantial amounts of unconventional resources such as shale gas that were previously non-recoverable or uneconomical to extract. With the development and acquisition of 4D seismic data, engineers have been able to more accurately map out accurately the evolution of fluids within the reservoirs. However, they have encountered the challenge to distinguish between hydrocarbons and injected fluids. Electromagnetic methods have attracted in the last decade substantial interest to exploit the sharp resistivity contrast between hydrocarbons and water, enabling it to track water fluid fronts, optimize injection, thus improving production rates. Conventional approaches to incorporate electromagnetic data into history matching processes have been to invert these data for reservoir parameters and apply those as constraints in the matching process. This approach faces however the challenge that the computational resources required for the inversion may be significant in addition to the requirement for manual post-processing to ensure meaningful interpretation. In this work we present a novel approach for incorporating a full wave electromagnetic time domain solver in which electromagnetic data are directly included in the history matching process. The full wave modeling enables higher accuracy representation of the underlying structures and its inclusions returns significantly better matchings and forecasts.

Introduction

Reservoir management has become a quintessential element for coping with the ever increasing demand of emerging countries such as China, Brazil and India and the increasingly more cost-intensive and complex extraction of oil and gas from newly discovered reservoirs. The later development is illustrated in the deep-sea explorations in the Gulf of Mexico and Arctic that has pushed technology to the limits and necessitates the increase of recovery rates beyond the current rate of 30 %. Understanding the movement of injected water and hydrocarbons within the reservoir via simulations incorporating field data has been key for increasing recovery rates. Electromagnetic techniques have attracted in the last decade significant attention in the oil and gas industry for its ability to overcome some of the shortcomings of seismic techniques (such as mapping of reservoirs beneath salt layers), and also because it is applicable in areas where governmental regulations forbid the employment of seismic equipment [1], [2]. While resistivity well logging has long been a standard method for determining hydrocarbon reservoirs when drilling for oil, controlled-source electromagnetic methods and crosswell electromagnetic tomography have been at the forefront of the advancement of electromagnetic techniques following the increasing computational resources and advances in technology. Controlled source electromagnetic (CSEM) [3] surveying arose from academic studies of the oceanic lithosphere in the 1980s but has initially attracted limited attention due to low oil prices, shallow water environments and the success of 3D seismic methods. Starting with trials conducted by Statoil and ExxonMobil in the late 1990s in deep water and successful reservoir resistivity evaluations in deep offshore Angola have resulted in a swift growth of the employment of these techniques, especially in deep offshore environments. Crosswell electromagnetic tomography has originally originated from the experiments conducted in the 1970s for detecting tunnels in Korea. Although effective for hard rock, high attenuation in soft rock environments caused by high-frequency wave transmissions (megahertz range) hampered its employment. While lower frequencies encountered less attenuation, they suffered from dispersion and couldn't be used to image with traditional techniques. Advances in electromagnetic technology have however led to the development of low frequency receiver technology that consist of a magnetic field sensor and lock-in amplifier and is able to reject incoherent background noise, while coherent signals are amplified and measured [4]. Building upon the achievements obtained by Wilt et. al. [4], [5], Marsala et. al., [6] conducted trial experiments in the Haradh field in

Saudi Arabia to map the fluid distribution and monitor the movement of injected water, achieving high quality EM data for even large well separations of more than 850 m.

Figure 1: EM Crosswell Tomography. Strong distinguishability between hydrocarbons and water are achieved.

With the advances in crosswell electromagnetic imaging, there has also been the need to improve processing and interpretation of the data. Conventional approaches simplified Maxwell's equation to a second order partial differential equation and invert this equation for the conductivity distribution. Despite the significant progress in developing new algorithms for the inversion problem [7], [8], [9], the non-uniqueness of the solution [10], the requirement for significant computational resources (especially for large scale problems) and necessity to manually fine tune parameters may render these approaches less appealing to modern history matching systems.

While history matching has been a manual task with an engineer manually fine-tuning parameters in order to match simulation results to the real production parameters, current history matching has been highly automatized in order to cope with the ever increasing amount of data and tighter forecast update time frames [11], [12]. Optimization algorithms were then employed for history matching, such as Bittencourt et. al. [13] incorporating a genetic algorithm for optimizing reservoir development. Data assimilation (DA) schemes have attracted recently significant attention as rising complexity have pushed conventional optimization methods to the limits. The Ensemble Kalman Filter (EnKF) has been at the forefront of this development due to its ability to cope with nonlinearities, its efficient implementation and versatility [14]. The EnKF approximates the covariance matrix of the system via an ensemble covariance matrix that significantly reduces size and computational complexity. In the article by Aanonsen et. al., [14] an extensive overview about the application of EnKF in reservoir engineering was presented focusing primarily on the incorporation of production data [15], [16], [17]. With production data having been readily incorporated, there has been the desire to incorporate electromagnetic data to exploit the strong resistivity contrast for obtaining better forecasts and reducing ensemble spread.

Focusing on the electromagnetics we have developed a FDTD based reservoir history matching scheme that incorporates time lapse electromagnetic field recordings in 2D into the observation operator for reservoir forecasting. The framework consists of a black oil reservoir simulator that is interfaced to an Ensemble Kalman Filter scheme for matching simulated data to the observations. The framework can be applied to arbitrary heterogeneities and simulations results show a significant improvement in forecasting.

Methodology

The developed framework is illustrated in Figure 2 and integrates a 2D finite difference black oil reservoir simulator MRST [18] together with a 2D highly efficient finite difference time domain electromagnetics solver into an EnKF. The EnKF performs the history matching and forecasts the next state that is then returned back to the reservoir simulator.

Reservoir Simulation

The 2D finite different black oil reservoir simulator models a two-phase flow problem for oil and water phases that are described by the system of equations

$$\nabla \cdot v = q, \quad v = -K (\lambda \nabla P + (\lambda_w \rho_w + \lambda_o \rho_o) g \nabla z), \quad (1)$$

$$\phi \frac{\partial S_w}{\partial t} + \nabla \cdot (f_w(S_w) + [v + \lambda_o (\rho_o - \rho_w) g \nabla z]) = q_w, \quad (2)$$

with ρ_o and ρ_w denoting the density of oil and water phase, λ_o and λ_w the saturation dependent mobilities and $f(w)$ the fractional flow of the water phase. S_w and S_o are the water and oil saturation with $S_w + S_o = 1$, q the flux, v Darcy's velocity, g the gravity, K the permeability tensor and P the pressure within the reservoir. For convenience we have neglected

capillary effects, and due to the 2D model structure gravity effects are also neglected. The system is solved iteratively by first computing the pressure distribution within the reservoir that is then substituted for advancing the saturation in time.

Figure 2: History Matching Framework

Electromagnetic Model

In order to couple the reservoir simulator and obtain the conductivity profile for the electromagnetics solver, we employed different variations of Archie's Law for transforming porosity, saturation and salt concentration into conductivity. The salt concentration is assumed to be constant during the simulation, justified by the use of a constant water injection making the chemical reactions of NaCl negligible.

Archie's Law was developed by Guus Archie in 1942 and forms an empirical relationship stating that the logarithm of conductivity is linearly related to the logarithm of porosity and saturation, as

$$\log(C) = \log(C_w) + m \log(k \phi) + n \log(S) \quad (3)$$

with C_w being the scaled water conductivity, ϕ and S the porosity and saturation. The parameters k , n and m are empirically retrieved constants. Besides the original model proposed by Archie, there have been several other formulations that differ from Archie's original equation in terms of the parameter values. To illustrate the robustness of the presented framework in terms of different conductivity models, we have performed forecasts for several different models and averaged their results, hence extending our analysis beyond the general convex Archie's original formulation. The models most widely employed in the industry and used in this study are given by Archie [19], Winsauer [20], Tixier [21], Carothers [22], Timur [23] and Hill [24] where the conductivity of the injected water C_w are given by the IJWC-Equation [25]

$$C_w = \left[\left(0.0123 + \frac{3647.5}{S_{wc}^{0.955}} \right) \frac{8.2}{0.18 T + 3.9} \right], \quad (4)$$

with S_{wc} being the salt concentration (in ppm) and T the temperature (in Celsius) in the formation.

Having obtained the conductivity distribution we engage into a crosswell electromagnetic experiment via solving Maxwell's equation for a crosswell source-receiver setup. Maxwell equations are the fundamental equations for the propagation of electromagnetic waves and are composed of four different physical laws. These are Faraday's Law

$$\nabla \times \mathbf{E} = - \frac{\partial \mathbf{B}}{\partial t}, \quad (5)$$

Ampere's Law

$$\nabla \times \mathbf{H} = \mathbf{J} + \frac{\partial \mathbf{D}}{\partial t}, \quad (6)$$

Gauss' Law for the Electric Field

$$\nabla \cdot \mathbf{D} = \rho, \quad (7)$$

and Gauss' Law for the Magnetic Field

$$\nabla \cdot \mathbf{B} = 0, \quad (8)$$

with $\mathbf{E}$ denoting the electric field, $\mathbf{H}$ the magnetic field, $\mathbf{D}$ the electric displacement, $\mathbf{H}$ magnetic field and $\mathbf{B} = \mu \mathbf{H}$ with μ the magnetic permeability. We employ the first order method Finite Difference Time Domain (FDTD) with PML boundary conditions [26], that allows us to resolve arbitrary heterogeneities and extends the generally performed simplifications (e.g., [7], [27], [28]). We assume the setup of Marsala et. al., [6], computing electric and magnetic fields, retrieve their time lapse differences and incorporate these into the observation operator.

History Matching

As presented in the introduction, we have implemented the EnKF that was first introduced by Evensen et. al. [29], and represents the distribution of the system state via a collection of state vectors (ensemble) that approximates the covariance matrix of the system by a sample covariance matrix computed from the ensemble. Despite the fact that the EnKF updates are based on means and covariances only (i.e., second order statistics neglecting higher order moments of the joint probability density distribution of the model variables) and are computed from a finite size ensemble, impacting the quality of the history matching estimates, the EnKF has shown to work remarkably well in practice [14], [30]. Achieving good matching for a variety of different problems, the EnKF has naturally become one of the methods of choice for reservoir history matching.

To achieve efficient computation and handle nonlinear observations we have resorted to an observation matrix-free implementation of EnKF. Given N_e the ensemble size and $X = [x_1, \dots, x_{N_e}]$ the state ensemble matrix, with x_i denoting the state vector of the i -th ensemble member. Each ensemble member consists of permeability, porosity, water saturation and pressure distribution within the reservoir. In addition, we define the scaled covariance anomaly $A = X - \frac{1}{N_e} (\sum_{i=1}^{N_e} x_i) e_{1 \times N_e}$ with $e_{1 \times N_e}$ denoting the matrix with ones as elements and size $1 \times N_e$ and $[H]_{:,i} = h(x_i) - \frac{1}{N_e} \sum_{j=1}^{N_e} h(x_j)$ the observation matrix with $h(x_i)$ being the nonlinear observation for the i -th ensemble state vector. Then for the data matrix D and its corresponding ensemble covariance matrix R , the EnKF update step can be written as:

$$X^a = X^f + \frac{1}{N_e} A H^T \left(\frac{1}{N_e - 1} H H^T + R \right)^{-1} (D - h(X^f)) \quad (9)$$

with X^f being the forecasted ensemble state obtained by integrating each ensemble member in time using the reservoir simulator. For further details about the EnKF the reader may refer to the review article of Aanonsen et. al. [14].

Simulations

In this section, we present an extensive study and analysis for five different test cases that differ in total simulation, history matching and update times. The reservoir under consideration consists of a Cenozoic sedimentary rock structure [31] in which we assumed that reservoir rock is sandstone. The porosity and permeability values, linked by a poro-perm relationship, are obtained from initial simulations via Petrel. The porosity values range between 11 and 32 percent, and the permeability values lie in the range between 132 to 872 milli darcy. For the ensemble we generated 80 models of porosity and permeability distributions with the porosity and permeability values lying within the corresponding ranges. The permeability tensor for all realizations is assumed to be diagonal with

$$K = \begin{pmatrix} k & 0 & 0 \\ 0 & k & 0 \\ 0 & 0 & \frac{k}{10} \end{pmatrix} \quad (10)$$

where k is the permeability value depending on the spatial position. For the injector-producer pattern we have used a five-start pattern that is commonly employed in modern oil field development [32] and can be easily used for extrapolation. The initial pressure levels within the reservoir were set at 5035 psi, with the pressure levels at the producer wells kept (4350 psi) constant and adjusting at the injector. The above described reservoir is then employed in a series of history-matching experiments that incorporate production measurements and electromagnetic data. The bottom hole pressure (BHP), water cut ratio (WCR) and production flux were measured at all wells, with standard measurement errors of 370 psi for BHP and around 7 % measurement error rates for the other production data. For electromagnetic measurements we have assumed an error rate of 2 %. For analysis purposes we have defined five test cases where measurement of production data are conducted every 30 days, and the electromagnetic measurements were taken during each data assimilation update period.

Test Case	Total Simulation Time	History Match Period	DA Update Period
1	16	8	5
2	20	8	5
3	24	8	6
4	24	10	7
5	24	12	8

Table 1 Test cases and their total simulation time, history matching period and update period.

The time frames conform to industry practice where electromagnetic surveys are economically justified every 4 – 8 years [33].

Analysis

In Figure 3 we show the oil production rates at the four producer wells for scenario 2 using the Archie model [19]. Both figures illustrate the matching enhancements and reduction in ensemble spread that result from the use of electromagnetic

surveys. In particular, the additional incorporation of electromagnetic data reduces the ensemble spread by around 2 years which presents a significant reduction in production uncertainty. The tighter ensemble spread is also represented in the matching improvement of 73.73 % as compared to sole production data matching.

Figure 3: Oil production of the four producer wells for the test case 2 using Archie's conductivity model with EM update (left) and without update (right).

Figure 4 Cumulative oil production for testcase 3 using Tixier's conductivity model with EM update (left) and without (right).

The significant improvement in the forecasting results can be also observed from Figure 4, showing the cumulative oil production rate of the field. A comparison between the two Figures clearly shows that the ensemble spread decreases from around 8000 sm³ to around 2000 sm³, providing significantly better forecasts, higher certainty in the amount of oil produced, and significant reduction in costs due to better resource allocation, reduction in penalty fees and steadier planning. Furthermore, wrong production decisions such as the initiation of EOR etc. may cause deterioration in the production levels and undesirable displacement of the hydrocarbons that may negatively affect potential reservoir recovery. This significant improvement is also reflected in the matching improvement of around 86.87 %, that further reflects the ability to better map the reservoir formation due to changes in the electromagnetic recordings.

Figure 5 Water cut ratios for test case 4 using Winsauer's conductivity model with EM (left) and without EM update (right).

Having considered oil production rates, we focus now on the production of water from the reservoir (see Figure 5). Water cut ratio is an important parameter in determining a change in production strategy as well as evaluating the need for additional wells for extraction and injection purposes. High water cut rates imply that the majority of the produced fluid is mainly water and the requirement to dispose the fluid may lead to further costs, that are particularly high in offshore locations. The general trend as presented before induces a reduction in uncertainty and matching enhancements attain around 51.63 % as compared to sole production data matching.

In order to study in detail how changes in the conductivity profile affect the electromagnetic field evolution, we present in Figure 6 the electromagnetic recordings for four different instances resulting from the different test cases. Electromagnetic waves attenuate much stronger for higher conductive media than for lower media of lower conductivity and this is clearly observable in the EM field recordings. This implies as well that changes in the conductivity during the simulation time are clearly observable in the EM field recordings, meaning that a decrease in the amplitude of the EM field is due to an increase in the conductivity. Following Archie's Law, this is caused by an increase in porosity and water saturation within the reservoir. In addition to the general increase/decrease of the conductivity of the formation, we are also able to determine 2D spatial changes by comparing the different receiver EM fields indicating the general conductivity distribution between them.

Figure 6: Comparison of the recording EM waves for a typical electromagnetic source (white point) and receiver (black dots) setup.

We present in Table 1 an overview of the average matching enhancements obtained from the simulations. The results clearly indicate an overall improvement in history matching from the inclusion of electromagnetic data, with most parameters and instances achieving improvement rates of more than 50 %. While the different test cases have different simulation, history matching and update times, in all cases electromagnetic data enable to reduce uncertainty, improve matching and provide better forecasts, regardless of the amount of production data or the forecasting time span. The primary reason for this improvement can be attributed to the interwell mappings that provide, in addition to the data from the individual wells, conductivity changes between the different wells and hence more accurate knowledge about the formation. As discussed above increases in porosity and saturation lead to an increase in conductivity that subsequently lead to higher attenuation of the electric fields that can be recorded. Performing 2D simulations and recording the electric fields at several different locations, one can determine the changes between the source and receiver and deduce the general evolution.

Average Matching Enhancement (compared to production data matching only)

	Case 1	Case 2	Case 3	Case 4	Case 5
Oil Prod. (Avg Wells)	74.81 %	74.81 %	73.36 %	52.84 %	70.20 %
Water Cut (Avg Wells)	74.42 %	74.28 %	74.24 %	51.65 %	76.73 %
Injector Pressure	0.01 %	0.003 %	88.03 %	68.99 %	75.89 %
Cumulative Oil Prod.	80.72 %	78.49 %	86.70 %	57.83 %	49.28 %
Cumulative Water Cut	78.61 %	78.36 %	82.29 %	59.60 %	76.12 %

Table 2: Average matching enhancement compared to only production data matching for the 5 different cases.

Conclusion

In this work we presented a 2D Finite Difference Time Domain (FDTD) based update method for history matching that integrates time lapse electromagnetic data directly into an ensemble-based assisted history-matching scheme. We have introduced several different petrophysical models that illustrate the robustness of the proposed framework for various different simulation and update times. The framework has the following advantages with respect to alternative approaches:

- The method is highly versatile and flexible with respect to different well patterns
- Electromagnetic data are more sensitive to changes in porosity and water saturation and hence can reduce significantly ensemble spread and provide more accurate forecasts
- The direct inclusion of electromagnetic data avoids computationally expensive and ill-conditioned inverse problems.
- The full wave approach ensures that electromagnetic wave propagation is captured as accurately as possible.

The simulation times can be easily controlled and the total simulation time for around 20 years has been around 15 minutes, making the presented framework an efficient approach for reservoir forecasting.

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