Synergizing Crosswell Seismic and Electromagnetic Techniques for Enhancing Reservoir Characterization

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Summary

Increasing complexity of hydrocarbon projects and the request for higher recovery rates have driven the oil-and-gas industry to look for a more-detailed understanding of the subsurface formation to optimize recovery of oil and profitability. Despite the significant successes of geophysical techniques in determining changes within the reservoir, the benefits from individually mapping the information are limited. Although seismic techniques have been the main approach for imaging the subsurface, the weak density contrast between water and oil has made electromagnetic (EM) technology an attractive complement to improve fluid distinction, especially for high-saline water. This crosswell technology assumes greater importance for obtaining higher-resolution images of the interwell regions to more accurately characterize the reservoir and track fluid-front developments. In this study, an ensemble-Kalman-based history-matching framework is proposed for directly incorporating crosswell time-lapse seismic and EM data into the history-matching process. The direct incorporation of the time-lapse seismic and EM data into the history-matching process exploits the complementarity of these data to enhance subsurface characterization, to incorporate interwell information, and to avoid biases that may be incurred from separate inversions of the geophysical data for attributes. An extensive analysis with 2D and realistic 3D reservoirs illustrates the robustness and enhanced forecastability of critical reservoir variables. The 2D reservoir provides a better understanding of the connection between fluid discrimination and enhanced history matches, and the 3D reservoir demonstrates its applicability to a realistic reservoir. History-matching enhancements (in terms of reduction in the history-matching error) when incorporating both seismic and EM data averaged approximately 50% for the 2D case, and approximately 30% for the 3D case, and permeability estimates were approximately 25% better compared with a standard history matching with only production data.

Introduction

History matching and reservoir forecasting are key areas in the oil industry for retrieving petrophysical parameters, matching reservoir models to the real reservoir data, and providing forecasts for proper business and reservoir-management decisions (Baker 2001). Reservoir history matching has been a common industry practice for many decades but has recently attracted even more prominence with increasing exploration costs and oil prices (Oliver et al. 2008). In the past, a manual task, with an engineer adjusting certain reservoir parameters to match simulated production curves to the real measurements, history matching recently became more automatized, using sophisticated optimization and statistical techniques (Oliver and Chen 2011). Chavent et al. (1975) applied the optimal control theory for determining reservoir permeability while matching pressure levels to the production levels. Cullick et al. (2006) introduced a global and nonlinear proxy optimization method for reservoir history matching to match the individual well-fluid rates within the reservoir.

Schulze-Riegert et al. (2002) illustrated the optimization characteristics of an evolutionary algorithm for improved matching. Although optimal-control methods and other optimization techniques gained prominence in the field, these techniques encountered difficulties in incorporating the increasing amount of data that are gathered, and may necessitate significant manual tuning for achieving optimal results (Aanonsen et al. 2009).

With the advances in reservoir-monitoring techniques, the industry has faced a new challenge in coping with the huge and multivariate data sets that are collected and incorporated into the history-matching process and the demand of companies to reduce the time for history matching. To face this new challenge, the reservoir community turned into data-assimilation methods used in the field of atmospheric and oceanic sciences to enable the efficient incorporation of large amounts of data for improved modeling and forecasting. Among these methods, the ensemble Kalman filter (EnKF) attracted significant attention because of its ability to cope with strong model nonlinearities, its reasonable computational complexity, and its robustness (Oliver and Chen 2011). One can find detailed reviews about the different forms and implementation aspects of the EnKF in Aanonsen et al. (2009) and Hoteit et al. (2012).

Because sparse spatial sampling of production data limits the effectiveness of the history-matching process, the incorporation of additional data was considered for overcoming this limitation. The 4D seismic gained prominence in monitoring the changes within a reservoir, with many studies using them for reservoir history-matching purposes (Skjervheim et al. 2007; Sedighi-Dehkordi and Stephen 2010; Leeuwenburgh et al. 2011; Kazemi et al. 2011; Trani et al. 2013). Skjervheim et al. (2007) successfully incorporated inverted time-lapse seismic data and production data into the EnKF for reservoir model updating, improving the permeability estimate for synthetic and real field cases of the North Sea. The method relies, however, on the prior interpretation of the seismic data that may differ from the actual reservoir state. Leeuwenburgh et al. (2011) history matched 4D seismic data by directly integrating seismic amplitude data into the process, avoiding the need for inversion and demonstrating improvements in reservoir forecasting (Gibson and Levander 1988; Yilmaz 2001). Even though convolutional methods are the standard techniques for surface seismic imaging, their ray-theory assumption is not always adequate for crosswell imaging (Sheriff and Geldart 1995; Gao et al. 2012). Therefore, a full-wave approach is needed (Choy et al. 1980). In a more recent article, Leeuwenburgh et al. (2011) history matched 4D seismic for the tracking of the fluid fronts of a 3D synthetic example, showing consistent multimodel history matching by means of the combined usage of production and seismic data. The seismic information was incorporated into the model by first inverting it for saturation levels and then using these attribute data for constraining the reservoir saturation with the EnKF. As for Skjervheim et al. (2007), prior interpretation of the seismic data and the deduction of the saturation profiles may be critical for this approach.

The previous discussed time-lapse surface seismic techniques were considerably applied for reservoir-monitoring purposes to determine waterflooding and to provide more-accurate geological descriptions (Lumley 2001; Emerick and Reynolds 2012). These techniques encounter different challenges such as limited

Fig. 1—Crosswell seismic tomography (a), crosswell EM tomography (b) and crosswell EM and seismic tomography (c). For seismic tomography, (a) a good differentiation between fluid and rocks is achieved, whereas hydrocarbons and water are less distinguishable. Electric fields are only weakly propagated in hydrocarbons compared with water and rocks, enabling EM techniques to distinguish clearly between injected fluids and hydrocarbons in a reservoir (b). A synergy of the strong differentiation between rocks and fluids (seismic) and hydrocarbons and water (EM) enables mapping out of hydrocarbons, water, and rock formations (c).

resolution, not being applicable in certain environments (e.g., close to buildings) (Yukon Corporation Seismic Imaging Report 2006), and facing processing challenges, such as imaging beneath salt layers (Hoversten et al. 1998; Leveille et al. 2011). To obtain a better understanding of subsurface reservoirs and to overcome some of the surface seismic challenges, crosswell seismic-imaging techniques attracted considerable attention recently (Schlumberger Imaging Services Report 2009, 2010; Daley et al. 2010; Marion et al. 2013). Crosswell seismic imaging places source and receivers in different wells, and records the acoustic waves at the receivers that are emitted by the source (Rector III 1995; Schlumberger Imaging Services Report 2010). The emitted seismic waves may experience different propagation patterns for the individual reservoir rocks that are detectable in the recordings at the receivers. Furthermore, changing fluid distributions induce a change in the arrival times and amplitudes of the seismic waves that are then exhibited in the seismograms. Despite significant technology advances, acoustic waves face the challenge that the seismic contrast between different fluids is rather low, and hence are limited in their ability to map out hydrocarbon fronts, as illustrated in Fig. 1. Focusing on overcoming the poor distinguishability between hydrocarbons and water, EM methods, such as crosswell EM tomography (Wilt and Alumbaugh 2003; Schlumberger Imaging Services Report 2009) and controlled source electromagnetics (CSEM) (Constable and Srnka 2007; Andréis and MacGregor 2008; Strack 2014), attracted attention because of the sharp contrast in conductivity between different fluids (Hu et al. 2009) (Fig. 1). EM-imaging techniques were actively pursued by De Pavia et al. (2008) to improve interwell mapping, reaching accurate resolutions for the interwell region lengths of even a kilometer (Marsala et al. 2008).

With seismic imaging being able to clearly distinguish between rocks and fluids, and EM methods, providing information for determining the content of fluids, engineers have been looking

to synergize the benefits of both methods to improve the imaging of the reservoir formation, as illustrated in Fig. 1, and enhance formation-fluid tracking (Rector III 1995; Hoversten et al. 2003; MacGregor et al. 2007; Chen et al. 2007; Hu et al. 2009; Newman et al. 2010; Moorkamp et al. 2011; Abubakar et al. 2012; Gao et al. 2012; Lien 2013).

In particular, Abubakar et al. (2012) proposed a joint-inversion approach to exploit the strong correlation between EM and seismic parameters through a petrophysical relationship, demonstrating superior performance compared with independent inversions of each data set. Gao et al. (2012) presented an extensive full-waveform study of the benefits of joint EM and seismic inversion and suggested that the joint-inversion method reduces the ambiguity on the determination of the porosity and fluid saturation. These studies primarily focused on the static inversion with a gradient-based technique, and did not consider the important uncertainty in porous-media flow parameters (e.g., permeability and transmissibility multipliers) crucial for accurately modeling and simulating the fluid displacement in the reservoir.

This work presents a reservoir history-matching system that incorporates a full-acoustic waveform solver and finite-difference time-domain EM solver for directly constraining the reservoir flow with crosswell time-lapse seismic and EM data. The presented approach differs greatly from the approaches of Gao et al. (2012) and Abubakar et al. (2012) in that the full-waveform data together with production data are directly incorporated into a reservoir simulator with an ensemble-based history-matching method. Making use of the full-reservoir dynamics, the approach aims toward the joint geophysical flow-parameter estimation and does not necessitate the separate inversion of EM and seismic data. This history-matching approach only requires forward reservoir and wave models, avoiding the need for gradient computation of the seismic and EM solvers compared with Gao et al. (2012), which makes the framework more flexible for different reservoir

Fig. 2—Flowchart representation of the history-matching framework.

formations and solvers. It further enables the estimation of the static reservoir parameters (e.g., permeability and porosity) as well as the dynamic variables (e.g., formation pressure and saturation), extending the approach proposed in Gao et al. (2012). In this paper, the system is outlined in the upcoming sections by first describing the reservoir simulators, then the geophysical crosswell imaging solvers, and concluded by describing the EnKF implementation and results.

Extensive history-matching experiments are conducted to illustrate the effectiveness of the proposed system and to outline the advantages of the direct integration of waveform data for enhancing geophysical flow-parameters estimation. The experiments were conducted with both 2D and 3D reservoirs. The simple 2D reservoir serves for providing a detailed understanding of the correlations between changes in the reservoir and the changes in the geophysical data. The realistic 3D reservoir further examines the framework for reservoir history matching of real reservoirs. The changes in the reservoir's saturation and pressure levels are well reflected in the geophysical data and lead to considerable improvements in history matching. Both static and dynamic reservoir parameters are shown to be better retrieved when incorporating the crosswell data compared with using solely production data. In addition, the system may be easily integrated with commercial reservoir simulators, as further discussed later. The strong performance of the framework and direct integration of the geophysical data, avoiding the separate inversion, make the framework an attractive method for large-scale reservoir history-matching applications.

Methodology

The developed history-matching framework outlined in Fig. 2 interfaces a reservoir simulator, for example, Matlab Reservoir Simulation Toolbox (MRST) (Lie et al. 2012) or Eclipse (GeoQuest 2014), and both full-waveform acoustic and finite-difference time-domain EM solvers through an EnKF directly with well-production data and equivalent geophysical observations. The framework starts from a geological model of the reservoir together with an initial ensemble of static reservoir parameters and then sequentially estimates the ensemble of both dynamic and

static reservoir parameters. At each update step, the reservoir parameters are estimated by each ensemble member and are transferred to the seismic and EM solvers. The time-lapse seismic and EM responses are then computed for each ensemble member, and sent to the EnKF module together with the collected reservoir data. The EnKF module updates the ensemble members with the reservoir data by back projecting the forecast errors into the model-state space, and the procedure is then reinitialized.

Reservoir Simulation. The 3D black-oil reservoir simulator Eclipse (GeoQuest 2014) is used for modeling the evolution of the three fluid phases (oil, gas, and water) within the reservoir subject to water injection (GeoQuest 2014). The black-oil equations follow the standard formulation for conventional reservoir modeling for hydrocarbon reservoirs and have exhibited an accurate representation of the dynamics in the subsurface (Trangenstein and Bell 1989) for waterdrive recovered reservoirs. The system is solved iteratively by means of the Newton-Raphson method, as implemented in Eclipse (GeoQuest 2014). For the 2D reservoir, the black-oil model was reduced to two phases (oil, water) and solved with MRST (Lie et al. 2012).

Full-Wave Acoustic-Wave Propagation Method. For the seismic survey, the porosity and saturations were transformed by means of Biot petrophysical transformation (Biot 1962) to velocity and density profiles of the formation and then used for in the full-waveform solver. Biot's theory (Biot 1956, 1962) deals with the propagation of acoustic waves in fluid-saturated porous solids. It was extensively applied for estimating acoustic-wave velocities in fluid-saturated media (Mavko et al. 2009). 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 oil extraction (Biot 1962). 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 (Biot 1956). Although Gassmann's equations were widely used because of their simplicity and correspond to the Biot velocities in the low-frequency limit, for high-frequency seismic waves, as

Fig. 3—Porosity (a), saturation (b), velocity profile (c), and density profile (d) for three different instances obtained with Biot's equations and their corresponding seismic recordings (V_p) at the source (solid line) and receiver location (dotted line). The seismic recordings exhibit the attenuation (approximately 19% for the green case) experienced for higher densities as well as the earlier arrival time for higher-velocity profiles. The additional oscillations experienced in the source receiver represent the reflections caused by the velocity and density changes.

encountered in crosswell seismic imaging (Schlumberger Imaging Services Report 2010), Gassmann's equations may underestimate velocities by approximately 10% (Nolen-Hoeksema 2000; Hoteit and Ravanelli 2014). With the full acoustic-wave propagation solvers, this may lead to significantly distorted seismic recordings and hence, misrepresentation of the formation structure. For the underlying reservoirs and crosswell seismic-tomography applications, the high-frequency assumption is valid (Mavko et al. 2009; Nalonnil and Marion 2012), and the P -wave velocity is represented by Biot (1962) and Mavko et al. (2009),

$$V_{P\infty} = \sqrt{\frac{\Delta + \sqrt{\Delta^2 - 4(\rho_{11}\rho_{22} - \rho_{12}^2)(PR - Q^2)}}{2(\rho_{11}\rho_{22} - \rho_{12}^2)}}, \dots (1)$$

where Δ, P, R, Q and $\rho_{11}, \rho_{12}, \rho_{22}$ are parameters computed from the effective bulk K_r , the porosity ϕ , the density of the rock ρ and fluid ρ_f , and the tortuosity parameter α . The parameters used in

Eq. 1 were computed from the equations outlined by Mavko et al. (2009). The shear effects encountered for crosswell imaging in fluid-saturated rocks are marginal, and hence, can be neglected in the simulation (Aminzadeh and Dasgupta 2013).

The velocity and density fields are then returned to the crosswell seismic-tomography setup, with a 1D full-waveform acoustic-wave propagation system solving the reduced rock-acoustic equations given by (Levander 1988)

$$\rho \frac{\partial^2 u}{\partial t^2} = \frac{\partial \tau}{\partial x}, \dots (2)$$

$$\tau = \lambda \frac{\partial u}{\partial x}, \dots (3)$$

where u denotes the displacements, τ the stress, and $\lambda = (\rho V_P)^2$ the first Lamé parameter (Mavko et al. 2009). Here, we implemented a robust fourth-order scheme, as presented in Levander et al. (1988). In Fig. 3, we present examples of recorded synthetic

Fig. 4—Synthetic conductivity cross sections (a) and its corresponding attenuation of the electric field in the figure (b). Because of the low frequencies that are applied, reflections from the different rock layers can be neglected, and solely the absorption represented by the conductivity is taken into account.

seismograms and the impact of different densities and velocities on the wave propagation. As observed in Fig. 3, increased velocity profiles lead to earlier arrival times of the seismic signal, whereas higher densities lead to increased attenuation.

As discussed previously, it is desired to use a full-waveform approach for modeling the propagation of seismic waves between the wells to accurately capture the resolution ranges of these techniques (Schlumberger Imaging Services 2010). The time-lapse differences resulting from comparing the seismograms of two consecutive surveys are then directly incorporated into the observation operator in the EnKF (see the History-Matching Method section).

Full-Wave EM Method. To determine the EM response of the formation, we transform porosity, saturation, and salt concentration to formation conductivity with variants of Archie's relation (Archie 1947). Archie's relation states that the logarithmic electrical conductivity $\log(\sigma)$ is related linearly to the logarithm of porosity and saturation, mathematically stated as

$$\log(\sigma) = \log(C_w) + m\log(k\phi) + n\log(S_w), \quad \dots \quad (4)$$

with C_w being a scaled water conductivity, ϕ and S_w the porosity and water saturation, and σ the electrical rock conductivity. The parameters m , n and k are empirically defined constants, and their values may vary significantly depending on the rock formation under consideration. We restricted our analysis to a sandstone rock formation with the parameters taken as those provided by Archie (1942). The conductivity of the injected water C_w was represented by the IJWC-Equation (Dresser 1982; Al-Attar et al. 2013)

$$C_w = \left[\left(123 \times 10^{-4} + \frac{36475}{10S_{wc}^{0.955}} \right) \frac{82}{1.8T + 39} \right]^{-1}, \quad \dots \quad (5)$$

with S_{wc} being the salt concentration (in ppm, assumed to be constant) and T the temperature (in celsius) in the formation. From the conductivity transformation, we then perform a realistic crosswell EM experiment by solving the Maxwell equations for a crosswell source-receiver setup. For a detailed discussion about Maxwell equations, the reader may refer to Peterson et al. (1998).

We present in Fig. 4 three different conductivity profiles (left) and the corresponding electric-field amplitudes (right) and outline the amplitude effect of the EM signal that was subsequently incorporated into the EnKF update step. As the solver is 1D, only a cross section of the reservoir is used for the calculations. After analyzing the figure, one sees that it shows that the electric fields exhibit stronger attenuation for higher conductivity values that is clearly visible in the sharper reduction in the amplitude for the blue curve compared with the green and red one.

We have used a first-order method finite-difference time domain (FDTD) with perfectly-matched-layer (PML) boundary conditions (Roden and Gedney 2000) to efficiently cope with arbitrary

heterogeneities. PML is an artificial absorbing layer to truncate the EM waves at the boundaries to avoid reflection, simulating problems with open boundaries. The usage of FDTD enables us to resolve arbitrary geometries and heterogeneities in addition to using the most general formulation ensuring wide applicability and adaptability. On the basis of the setup of Marsala et al. (2008), we simulated a source-receiver setting computing the electric and magnetic fields, then retrieving the time-lapse difference, before integrating these into the EnKF observation operator.

History-Matching Method. The developed history-matching framework is based on the EnKF. The EnKF is a sequential data-assimilation method that was introduced for efficient estimation of the large number of variables of complex nonlinear systems. It is further designed to efficiently integrate different types of data sets (Hoteit et al. 2012). The EnKF is a variant of the Kalman Filter on the basis of ensemble representations of the Kalman-filter forecast and analysis-error covariance matrices. More precisely, the filter-covariance matrices are estimated from the sample covariance of an ensemble of state vectors that represent the distribution of the system state. This considerably reduces the computational cost of the Kalman filter and allows its implementation with nonlinear models. The EnKF updates are solely on the basis of means and covariances (i.e., second-order statistics neglecting higher order moments of the joint-probability distribution of the model variables). Despite that, one can obtain acceptable history matches with relatively small ensembles (typically, between 50 and 100 members (Jafarpour and McLaughlin 2009)). The EnKF was further shown to perform reasonably well compared with other more-sophisticated, but more-costly, algorithms with realistic reservoir problems (Liu and Oliver 2005; Zafari and Reynolds 2005; Gao et al. 2006).

For further details about the EnKF and its variants, the reader may refer to the review articles of Aanonsen et al. (2009) and Hoteit et al. (2012).

Numerical Results

In this section, we first outline the experimental setup, then study the sensitivity of the proposed history-matching system to different experimental settings, and conclude with an examination of its overall performance.

Experimental Setup. We first introduce a 2D synthetic reservoir to illustrate the impact and dependence of the EM and seismic data on the dynamics of the reservoir, and explicitly outline the improvements. This is then followed by examining the performance of the method on a realistic 3D field that is a synthetic representation of a subpart of the Abqaiq field in Saudi Arabia. Unless otherwise noted, the same experimental setting was used in the 2D and 3D cases.

Fig. 5—Five-spot pattern with the injector well being in the middle and the producer wells around it for the 2D reservoir (Onwunali and Durlafsky 2011). The imaged cross sections are displayed in red (Marsala et al. 2011).

2D Reservoir. The 2D reservoir is 2 km in length, in the x - and y -direction, and 25 m in the z -direction, representing a Cenozoic sedimentary carbonate-rock reservoir structure, commonly found on the Arabian peninsula (Powers et al. 1966). Reservoir depth is 2000 m. The grid size is $40 \times 40 \times 1$. The reservoir rock is assumed to consist of carbonate rock with porosity and permeability values. For history matching, the reference permeability and porosity fields were obtained with unconditional simulation (Sequential Gaussian Simulation), incorporating an exponential variogram model. The permeability field was assumed to be log-normal distributed with mean 500 md and standard deviation of 200 md, and the porosity field was assumed to be normal-distributed with mean 25% and standard deviation of 3%. The anisotropy axes of the variogram model were 850 m in x -direction and 600 m in y -direction. We have then collected five samples from the reference permeability and porosity field to determine the sample variogram models for the ensemble generation. The corresponding variogram models were then used to generate 70 ensemble members. This ensemble size was set after a sensitivity study, showing that the rank provided by the considered ensemble is high enough for accurately approximating the filter covariance matrix, while small enough to enable efficient computation. The permeability values range from 150 to 1,000 md, and the porosities are in the range of 13 to 40% (Fig. 5), and these ranges were enforced in the permeability- and porosity-fields generation. The permeability tensor was assumed diagonal with $K_{xx} = K_{yy}$. The well pattern we considered is an inverted five-spot pattern (Fig. 6) (Bakan et al. 1991), consisting of one injector in the center and four producers at the corners. The initial pressure levels within the reservoir were set at 600 bar; producer wells had pressure controls equaling 300 bar, and the injector well was specified to inject $1500 \text{ m}^3/\text{d}$ of water. The viscosity of water was 1.4 cp, and it is 1.2 cp for oil. The state vector consists of the permeability, porosity, pressure, and saturation fields of the reservoir.

This 2D-reservoir test case is then used in a series of history-matching experiments (Fig. 7) that were used for forecasting pro-

duction and pressure levels while incorporating production, seismic and EM measurements. Bottomhole pressure (BHP), water-cut ratio (WCR), and production flux were measured at all wells, with measurement errors (Gaussian) of 25 bar for BHP and approximately 7% measurement error rates for the other production data. For seismic and EM measurements, we assumed error rates of approximately 10%.

We investigated different scenarios with the 2D-reservoir simulator that differ in their total simulation time, history-matching time, and the update times, as summarized in Table 1. Production data are history-matched every 30 days. EM and seismic surveys were incorporated at different time intervals (UT, update time), as summarized in Table 1. The time frames during which updates are performed conform to industry practices in which crosswell seismic and EM surveys may be conducted and are economically justified every three to seven years (Saito et al. 2006). Computational time for one 2D history-matching simulation was approximately 20 minutes, part of which a single (one ensemble member) EM and seismic simulation was approximately 1.5 and 1.55 seconds.

3D Reservoir. The modeled reservoir is displayed in Fig. 8 and represents a synthetic sector of the Abqaiq oil field (Powers et al. 1966; Edgell 1992; Simmons 2006). The reservoir encompasses six faults (as shown later in Fig. 11), has four different reservoir segments, four vertical injector wells, and six producing wells that are represented in Fig. 8. The reservoir is 9 km in length and 10 km in width, and exhibits a maximum depth of 2.8 km. The grid size is $29 \times 40 \times 5$. All wells are steel-cased and perforated with a plugback installed below the casing. The completion for the first injector well is provided in Fig. 9, and similar perforations were performed for the other wells.

The reservoir permeabilities and porosities were obtained, as in the 2D case, implying that the permeability tensor is diagonal. The permeabilities were assumed to be log-normal distributed with mean 1,300 md and standard deviation of 400 md, and the porosities were normal distributed with mean 16% and standard deviation of 8%. Reservoir-permeability values of the ensemble members range between 36 md and 10,000 md for K_{xx} , between 484 md and 9,500 md for K_{yy} , and between 1 md and 8,500 md for K_{zz} . The reference permeability field is plotted in Fig. 10. Porosity values of the ensemble members ranged from 1% to 28%, and the reference porosity field is represented in Fig. 10. The ranges of 10 to 10,000 md and 1% to 28% were enforced in generating all permeability and porosity fields. Both permeabilities and porosities fields were generated from an exponential variogram model with anisotropy axes of 500 m in the x -direction, 600 m in the y -direction and approximately 150 m in the z -direction. The initial ensemble fields were obtained with an exponential variogram model generated from well-log samples (11 wells in total) from the reference fields. The reservoir-fault transmissibilities were set to 1 (Fig. 11). The state vector consists of the full fields

Fig. 6—Reference permeability and porosity field for the 2D reservoir.

Test-Case Parameters			
Case	TSim (years)	HMT (years)	UT (years)
1	22	8	4
2	25	9	4
3	28	7	3
4	30	10	5
5	35	13	6

Table 1—Parameters of the five test cases considered for analysis (TSim = total simulation time, HMT = total history-matching time, UT = update time).

for the permeabilities K_{xx} , K_{yy} , K_{zz} , Porosity, Pressure, Water saturation, and Gas saturation. The total size of the state vector is $7 \times 5,800 = 40,600$ variables. Initial reservoir pressure was set at 200 bar, the bottomhole pressure (BHP) was kept at 400 bar at the injector wells, and the producer wells had a group target of producing $100,000 \text{ m}^3/\text{d}$. A total of 55 ensemble members was used, which were found to be sufficient to obtain reasonable history matching on the basis of a sensitivity analysis, and enabled us to achieve efficient computation. We used a history-matching time frame of 6 years, with update steps performed every 3 years, and further performed 10 years of forecasting. Observation error rates

Fig. 7—Examples of initial permeabilities of the ensemble members.

Fig. 8—Domain representation and well locations in the 3D reservoir.

Fig. 9—Well casing and perforation for injector Well 1 in the 3D reservoir.

Fig. 10—Reference permeability K_{xx} and porosity field of the formation for the 3D reservoir. Both permeability and porosity show strong heterogeneity in their values.

for the production data were set at 5% for all observations, whereas the observation error rates for seismic and EM data were set at 10% (Schlumberger Imaging Services Report 2009, 2010). Computational time for one history-matching experiment was approximately 2 hours on a supermicrocomputer with a single CPU, with the single (one ensemble member) seismic and EM simulations taking approximately 2.5 and 2.6 seconds.

The bubblepoint pressure was set to 300 bar, and there is a small gas cap in the 3D model. Because of the high injection-pressure levels, the pressure in the reservoir is fairly well maintained, leading to only a small development of gas. Changing gas saturations primarily affect the density levels in the seismic model; however, the setup ensures that gas generation does not mask the time-lapse seismic signal. For the EM signals, gas does not affect them at all because the electrical conductivity of the rock is primarily affected by the salt concentration of the water phase.

Other Experimental Configurations. In practical applications of crosswell imaging, wells that are farther than 2 kilometers apart may not be accurately imaged and were not taken into account in both the 2D and 3D reservoirs (Marsala et al. 2007; Schlumberger Imaging Services Report 2010). This implies that the cross section between Injector I01 and I02 is not considered, whereas the cross section between Producer P09 and Injector I01 is. We further assumed that for each update step, the crosswell imaging was performed sequentially for the individual wells during a time frame of 1 to 2 months and therefore does not require a total halt of the field production. On the basis of a sensitivity analysis, we could conclude that the temporal differences over which the EM and seismic surveys are conducted only marginally affect the signals, and the data were history-matched at the same UT (Schlumberger Imaging Services Report 2009, 2010; Marsala et al. 2011; Schlumberger 2013). Attenuation effects for both crosswell EM and seismic imaging were taken into account, as outlined in the Full-Wave Acoustic-Wave Propagation Method and Full-Wave EM Method sections. Although the one-dimensionality of the forward models may neglect 3D reflections and interference effects,

these effects are expected not to significantly alter the responses from the geophysical techniques for the considered scales compared with surface imaging. The time-lapse seismic and EM data were incorporated into the EnKF update step in nondimensional form (as percentage difference between the base survey and update time survey) which led to adequate history matches for the considered test cases compared with the normal integration of these data, as outlined in Skjervheim et al. (2007). The seismic data are compared as traces rather than maps. For each crosswell imaging distance, we have incorporated the seismic trace as recorded at the receiver. For EM data, we have incorporated the electric-field recordings, as outlined, for example, in Fig. 3. The number of data for EM and seismic was approximately 500 each.

Salt concentrations were assumed to be constant throughout the reservoir, as typically considered in the industry (Marsala et al. 2007; Schlumberger Imaging Services Report 2009; Zhdanov 2010). Even though, for resistivity logging, the salt concentration close to the wellbore may considerably change when injecting water (Alpak et al. 2006), the salt-concentrations differences within the reservoir may be rather insignificant for crosswell reservoir applications, or necessitate a more-comprehensive treatment, incorporating the chemical reactions the salt undergoes in the reservoir (Marsala et al. 2008).

The matching improvements were evaluated by comparing the root-mean-squared errors

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i^{\text{ref}} - y_i^{\text{est}})^2}{N}}, \dots \dots \dots (6)$$

for the individual cases. In Eq. 6, y_i^{ref} is the i th component of the considered reference attribute, and y_i^{est} is its corresponding estimate calculated from the ensemble. We have also analyzed the spread of the ensemble that represents the uncertainties about the filter estimate (Liu et al. 2009; Hoteit et al. 2012).

To simplify the notations and referral, we will denote the history-matching experiments with ElectroMagnetic and SEismic surveys by EMSE, SEON for SEismic ONLY surveys, EMON for ElectroMagnetic ONLY surveys, and PROD for solely using PRODUCTION data. In all these experiments, production data are history matched as well. The history-matching enhancement was computed as

$$MI = \frac{RMSE_{\text{Ref}} - RMSE_A}{RMSE_{\text{Ref}}}, \dots \dots \dots (7)$$

where $RMSE_{\text{Ref}}$ is the RMSE of the reference case, that is, only history-matching production data, and A is either EMSE, EMON, or SEON.

Experimental Results. In this section, we examine the performance of the presented framework on the 2D and 3D test cases, and outline the improvements resulting from synergizing crosswell EM and seismic data.

Fig. 11—Representation of the fault lines within the 3D reservoir.

Fig. 12—Production curves for the four producing wells (Case 1) without (a) and with (b) the incorporation of seismic and EM data, and scatter plots comparing the final estimated permeability vs. the reference permeability field with 70 ensemble members and without (c) and with (d) the incorporation of seismic and EM data. Regression analysis for the permeability estimates vs. the reference permeability shows a significant better matching of the data with the R^2 value of 22 percentage points higher for the experiments with the incorporation of seismic and EM data. (blue curve = mean of ensemble, gray curves = individual ensemble members, red curve = real total field production, magenta line = end of history matching).

2D Reservoir. We present in Fig. 12 the oil-production rates for the four producer wells, and a regression analysis for determining the relationship between the estimated permeability field vs. the reference field. In comparing the individual wells, the incorporation of seismic and EM data aligns the individual ensembles closer to the reference production curve (red), and significantly reduces the ensemble spread. The impact is especially outlined for the individual ensemble production rates for the first well, where some of the ensemble members exhibit a steep rise and subsequent drop in the rate for the history-matching case of only production data that are not observed in the reference production curve. In contrast, this development is not observed when incorporating seismic and EM data. Comparing the RMSE errors for EMSE and PROD indicates that the additional incorporation of seismic and EM data leads to a reduction in the RMSE error by 67.82%. A further aspect is the strong improvement in the estimation of the permeability field that exhibits a stronger relationship between the permeability values of the reference field and the estimated ones. The improvement is displayed in the higher R^2 value of the linear regression curve, implying that the estimated permeabilities align closer to the reference permeabilities.

We further present in Fig. 13 the gradual improvement resulting from the estimation of the total field production with the incorporation of seismic and EM data and the consequent reduction in

uncertainty. Although the history matching of only production data may induce a significant underestimation of the total-field oil production, leading to losses in recoverable quantities of oil and hence revenues, additional information from seismic and EM data helps reducing uncertainty, improves the estimation of reservoir parameters, and leads to more-accurate predictions of the reservoir properties. These improvements are outlined in the enhancements in history matching by 80.68% for EMSE, 67.81% for EMON, and 25.09% for SEON, respectively, compared with PROD.

The improvements observed previously are exemplified in the tracking of the water-saturation fronts, as displayed in Fig. 14. Focusing on the water saturation fronts for 56% and 58%, the estimated front with both EM and seismic data (in red) approximates more accurately the reference front (cyan) compared with when only production data are history-matched. The contrast in the quality of water-front tracking is strong close to the fourth producer where PROD estimates a faster front displacement compared with the reference front, whereas EMSE avoids this overestimation. The faster advancing water fronts for PROD are reflected in the underestimation of the total field production, as discussed previously.

The improvement in the history matches resulting from the synergy of seismic and EM data can be traced back to the significant dependence on changes in the water-saturation levels in the

Fig. 13—Production curve for the total-field oil production (Case 1) displaying the impact the different data sets have on the matching improvement. In all cases, production data were assimilated, and an ensemble size of 70 was used. A comparison between the different cases indicates the reduction in ensemble spread and tighter alignment of the estimated curve to the reference-field production. Both seismic and EM data were provided by the full waveform surveys. (blue curve = mean of ensemble, gray curves = individual ensemble members, red curve = real total-field production).

Fig. 14—Reference water-saturation profile and a comparison of the corresponding water-saturation fronts for 56% (outer curves) and 58% (inner curves). The cyan curves represent the reference saturation front; the red curve represents the saturation fronts resulting from the incorporation of production, seismic, and EM data; and black curves represent the front resulting from the incorporation of only production data (Case 1).

reservoir. Although the individual incorporation of either seismic or EM data improves the estimates of the saturation levels, the joint integration of these data sets helps to obtain greater distinguishability between the different phases, and hence significantly better estimates. This leads to better estimates of the water-saturation distribution and permeability. Furthermore, seismic data seem to be more-sensitive toward porosity compared with changes in the fluid levels, which can be explained from the rather insignificant density contrast between oil and water. In contrast, EM data showed a strong dependence on the water-saturation changes, which is consistent with Archie's relation. EM data depend strongly on the water-saturation levels in the reservoir and therefore may more easily distinguish between heavily and less heavily waterflooded reservoirs (Marsala et al. 2007, 2011; Lien 2013) that is rather challenging with seismic techniques. Furthermore, because of the strong salt-concentration dependence of the EM signal, EM techniques are further able to distinguish between water influx from an aquifer and the water that is injected from the surface (as outlined in the 3D case) because of the significant salt-concentration difference between the two fluids. Aquifer water has typically a salt concentration of approximately 100,000 to 200,000 ppm, whereas injected water is typically seawater and hence has a concentration of approximately 30,000 ppm (Abdel-Aal et al. 2003; Liu et al. 2009).

The horizontal spatial resolution of crosswell techniques is approximately 1 to 30 m for seismic (Schlumberger 2013) and 5

Fig. 15—Comparison of the mean permeability estimates resulting from the incorporation of the individual data sets (Case 1).

to 50m for EM (Schlumberger Imaging Services Report 2009), which, for the considered reservoir, is below the resolution of the reservoir simulation grid. This, in particular, allows crosswell seismic techniques to sufficiently detect the propagating water fronts in the previous case, whereas the strong resistivity contrast between the hydrocarbon and the water phase assists EM in compensating for the lower resolution compared with seismic and to determine more accurately the water-saturation levels between the wells.

The improvements in the estimation of the water-saturation fronts are reflected in the permeability estimates of the field, as shown in **Fig. 15**. The estimates gradually improve with the incorporation of seismic and EM data, with seismic data capturing the high-permeability values in the center, EMON and EMSE mapping out the high-permeability stretches in the center, and also EMSE capturing the high-permeability area in the North.

Although the incorporation of only production data leads to a rather smooth profile that represents a poor estimate of the reference permeability field, the incorporation of additional spatial information from seismic and EM data leads to a sharper and spatially heterogeneous estimate that better reflects the features of the reference heterogeneity.

Table 2 and **Fig. 16** summarize the matching enhancements for the important reservoir production parameters. The improvements are quantified by comparing the RMSE error for the considered cases with the RMSE resulting from history matching only production data. As **Fig. 16** exemplifies, history matching full waveform seismic and EM data considerably improves the reservoir estimates with enhanced saturation front tracking and better permeability estimates, among others. Accurate oil-production estimates are of great significance to determine the total field-production output, to forecast production declines, and for the optimal initiation of secondary

Average Matching Enhancement (with respect to PROD %)			
Parameter	SEON	EMON	EMSE
Test Case 1			
Oil prod. (avg. wells)	10.33	51.61	67.82
Water cut (avg. wells)	11.68	51.88	67.62
Pressure level	22.48	58.13	72.81
Total-field prod.	25.09	67.81	80.68
Total-field water cut	23.59	63.01	77.13
Test Case 2			
Oil prod. (avg. wells)	5.72	60.17	68.53
Water cut (avg. wells)	5.87	59.96	67.62
Pressure level	1.75	62.75	65.05
Total-field prod.	7.31	73.62	81.24
Total-field water cut	6.92	66.25	74.97
Test Case 3			
Oil prod. (avg. wells)	18.91	50.02	53.90
Water cut (avg. wells)	18.12	50.43	53.74
Pressure level	20.60	52.93	43.43
Total-field prod.	30.55	65.84	69.15
Total-field water cut	29.30	60.31	62.48
Test Case 4			
Oil prod. (avg. wells)	21.13	55.79	60.36
Water cut (avg. wells)	21.16	54.73	59.66
Pressure level	26.71	46.48	36.53
Total-field prod.	33.02	69.83	71.40
Total-field water cut	28.94	62.41	63.85
Test Case 5			
Oil prod. (avg. wells)	30.68	35.45	59.36
Water cut (avg. wells)	21.27	35.79	58.68
Pressure level	15.50	24.29	37.15
Total-field prod.	24.37	59.27	80.52
Total-field water cut	38.43	60.37	64.07

Table 2—Average matching improvements for different production parameters and four considered scenarios showing the considerable reductions in the RMSE errors with incorporation of crosswell data. For each row, the largest improvement is indicated in bold.

and tertiary oil-recovery strategies. Water-cut rates are important to determine the water content of the produced fluid, which is an important indicator for when to shut down a well. Improvement rates for EMSE are more than 50% for the majority of the parameters, which indicates the significance of additional information from crosswell seismic and EM surveys.

For Test Cases 3 and 4, the history-matching enhancements of the pressure levels for EMON outperform those of EMSE. The

primary reason for these cases is that the joint integration of EM and seismic data leads to significantly better matches for the flow properties, but causes the pressure levels at the injector well to be not as well matched compared with the use of solely EM data. This is likely because of the reduced impact of the BHP observations in the update step and the more refined overall estimates of the pressure levels within the reservoir with a trade-off that is a stronger average pressure profile at the injector well, causing the poorer match. This is confirmed by comparing the RMSE between the reference and estimated pressure fields, where the RMSE for EMSE is lower than the one for EMON by several bars.

Furthermore, the larger improvements for the history matching of EM data compared with seismic data may suggest a stronger differentiation between hydrocarbon and water fronts compared with when seismic data are history-matched. This is consistent with the results of Constable and Srnka (2007), Andréis and MacGregor (2008), Ellis et al. (2011), and Strack (2014). Even though seismic techniques have been widely applied and remain the most important exploration and monitoring technique, the strong fluid discrimination of EM techniques may lead to better interpretation. The results also demonstrate the benefits of combining seismic and EM data for enhanced reservoir history matching (Orange et al. 2009; Gao et al. 2012).

3D Reservoir. The results presented previously outlined the significant potential of synergizing EM and seismic crosswell data for enhancing reservoir history matching with the case of a 2D reservoir. Examining performance with a more-challenging and realistic 3D reservoir is presented in this section. To outline the reservoir flow dynamics and the complicated propagation patterns, we present the reference saturation levels of the reservoir at different times during history matching in Fig. 17. The figure plots the gradual water-saturation evolution in the domain caused by water injection from the injector wells, as outlined in Fig. 8.

Fig. 16—Matching improvements comparison for the joint incorporation of EM and seismic data vs. their individual incorporation. The blue dots indicate the improvements of SEON vs. EMSE, and the green dots show improvements of EMON vs. EMSE.

Fig. 17—Graphical representation of the saturation levels for oil (green), water (blue), and gas (red) for 2006, 2009, 2012, and 2015.

The water penetrates the individual sections of the reservoir, pushing the oil toward the producer wells, and leads to a gradual saturation of the domain. Fig. 18 plots the saturation levels after three years for different ensemble members. The high water saturation that is prevalent at the lower left of the reservoir is significantly less prevalent for the case on the right, outlining the strong heterogeneity and high uncertainty in the model solution that may result from initial uncertainties in the reservoir parameters.

After showing the strong variation for the ensemble members, we analyze the performance of the history-matching system and the impact of a combined incorporation of seismic and EM crosswell data for better subsurface characterization. We first analyze the well productivity index (PI) for producer P09 shown in Fig. 19. The well PI measures the flow efficiency per bar into well and is an important indicator about the productivity of the well. Although the integration of crosswell data does not seem to be

Fig. 18—Comparison between the water-saturation levels for the P05 (low-permeability) and P95 (high-permeability) model of the initial ensemble in 2009. A comparison clearly outlines the much lower water-saturation levels for the low-permeability region (left) compared with the high-permeability region.

Fig. 19—Comparison of the history-matching results for the well PI or Producer P09. The red curve indicates the real production levels, the blue curve indicates the mean estimate of the ensembles, the two cyan curves represent the P10 and P90 intervals, and the magenta line indicates the end of the history-matching period.

that beneficial within the first 2 years, starting from Year 3, the integration of crosswell data proves beneficial to avoid the considerable underestimation of the PI that may be as much as 500 $\text{sm}^3/\text{d}/\text{bar}$. This is of particular relevance because higher-than-expected well productivity may lead to higher production quantities that have to be processed on the surface, requiring sufficient volume capacity.

We further outline in **Fig. 20** the oil in place (OIP) in the field, which provides an indication about the remaining quantities of oil that may still be recoverable. Comparing the individual estimates suggests that, when only production data are history-matched, the OIP estimates may substantially exceed the reference reserves (by approximately 30,000 sm^3), suggesting higher quantities of hydrocarbons to be present than actually available. This is, in particular, relevant for enhanced oil recovery (EOR) initiatives that may not be economically justified because of the actual low amount of recoverable oil compared with the estimated one.

In **Fig. 21**, the well oil production for Producer P05 is presented. Even though the history matches are equivalent for the first 10 years, starting from Year 10, the integration of crosswell data assists in capturing the oil-production peak better compared with when only production data that are history-matched. The difference in the estimates for the PROD case is as much as 24% compared with 8% for the EMSE case. The main conclusion that can be drawn from this result is that the integration of seismic and EM data together may provide better estimates of the interwell water and oil saturation levels, in addition to providing refined estimates of the reservoir's permeability and porosity values, thereby indi-

cating the strong production increase in Well P09. Finally, we analyze the BHP level for Producer P01 (**Fig. 22**). When only production data are history-matched, the results indicate that the BHP in the well is approximately 5 bar lower than actually occurring. Integrating crosswell data remedies the underestimation effect and captures fairly well the reference-pressure profile.

We summarize in **Table 3** the matching improvement rates for a number of parameters for the considered test case. The selected reservoir parameters are critical for reservoir engineers to develop and characterize the reservoir formation. The incorporation of crosswell full-field data leads to a significant reduction in the RMSE error for the produced volume from the reservoir, as well as better forecasts of the water-injection rates into the reservoir. Accurate estimates for the total reservoir-volume production are important for improving reserve estimates and to better evaluate the economics of the field exploration. Likewise, determining accurately the amount of water that is injected into the reservoir becomes critical for estimating and forecasting water breakthrough and the disposal of the produce water.

As in the 2D case, we showed that the incorporation of seismic and EM crosswell data may lead to considerable improvements in the history matching of essential production parameters. It is, however, important to note that although one can clearly determine that the joint integration of both EM and seismic data leads to considerably better history matches, the performance of EM or seismic data alone may depend on the reservoir under consideration. The history-matching performance was fairly robust even for relative noise levels up to 30% for both seismic and EM data;

Fig. 20—Comparison of history-matching results for the field OIP. The red curve indicates the reference gas potential, the blue curve indicates the mean estimate of the ensembles, the two cyan curves represent the P10 and P90 intervals, and the magenta line indicates the end of the history-matching period.

Fig. 21—Comparison of history-matching results for the well oil-production rate for Producer P05. The red curve indicates the reference injection rate, the blue curve indicates the mean estimate of the ensembles, the two cyan curves represent the P10 and P90 intervals, and the magenta line indicates the end of the history-matching period.

Matching Improvement (with respect to Production)				
Parameter	Description	SEON	EMON	EMSE
FGIPG	Gas in place (gas phase)	14.64%	15.78%	20.54%
FPW	Field water potential	1.05%	0.99%	1.46%
FVPT	Total-reservoir volume production	38.69%	40.02%	44.71%
FWIT	Total-field water injection	50.12%	55.34%	63.37%
FWIR	Field water-injection rate	24.64%	27.16%	29.31%
FOIPL	Oil in place (liquid phase)	19.64%	18.87%	23.98%
WVPR (P09)	Well-voidage production rate (Producer 9)	24.16%	28.36%	33.13%
WVPT (P06)	Total well-voidage production (Producer 6)	18.89%	19.58%	20.08%
WPI (P05)	Water potential (Producer 5)	45.12%	46.58%	55.84%

Table 3—Selected parameters outlining the improvements in the RMSE errors in percentage (%).

however, for relative noise levels exceeding more than 40%, the history matches may significantly deteriorate. Relative noise levels of more than 30% are generally rather unusual and would indicate the necessity to re-perform the measurements (Schlumberger 2013).

Next, we further analyze the system performance for the retrieval of static reservoir parameters. For this, we present in **Fig. 23** the final permeability estimates. Comparing the estimate resulting from solely production history matching vs. the incorporation of crosswell data, one obtains a smoothened profile of the

permeability estimate when only production data are incorporated. This is primarily because the well data correlate weakly with the reservoir properties compared with the seismic and EM data and therefore lead to worse estimates of the permeability. This is quantified by the fact that the RMSE of the estimated permeability field by means of EMSE with respect to the reference field is approximately 25% better compared with the RMSE obtained when incorporating only production data. Finally, we outline in **Fig. 24** the final water-saturation estimates resulting from history-matching experiments with and without the

Fig. 22—Well BHP for Producer P01. The red curve indicates the reference injection rate, the blue curve indicates the mean estimate of the ensembles, the two cyan curves represent the P10 and P90 intervals, and the magenta line indicates the end of the history-matching period.

Fig. 23—Presentation of the estimated permeabilities with and without history-matching crosswell data and the reference permeability. The comparison illustrates the improvement in permeability estimate from the additional incorporation of crosswell data.

incorporation of crosswell data. As for the permeability, the estimates for the water saturation are considerably better, and the integration of both seismic and EM data assists in detecting the stronger flooding in the left figure at the bottom. The results can be partially explained by the considerably better estimates of the permeability field that result in enhanced fluid-propagation forecasts.

Conclusion

We have presented an EnKF-based reservoir history-matching framework for the incorporation of crosswell seismic and EM data obtained from full-waveform solvers. Crosswell-tomography methods have found applications in the petroleum industry for obtaining a more-accurate understanding of the subsurface geology, map hydrocarbon displacements and water fronts, and

Fig. 24—Presentation of the lowest layer of the reservoir for the final water-saturation levels. A comparison between the water-saturation distribution of the reference field and the one with and without crosswell data clearly outlines the more-refined saturation estimates.

refined permeability and porosity distribution estimates. We incorporated the full-waveform data directly for reservoir history-matching applications, avoiding the separate inversion of these data into subsurface attributes. The direct incorporation of these data considerably enhances reservoir history matches and subsurface estimates as outlined on synthetic 2D and 3D reservoirs test cases. The synthetic 2D provides a good understanding of the analysis of the matching improvements and the relation of the crosswell data with the reservoir dynamics. The 3D case further demonstrated that the technique delivers good history matches for realistic reservoir structures as well. Changes in the reservoir mass distribution are well reflected in the seismic and EM time-lapse signals and in the history-matching improvements for all studied cases. The results outline the potential of the direct incorporation of geophysical data for the matching and forecasting of field-production levels and better estimates of the subsurface parameters. The framework may allow, in realistic applications, one to obtain better average permeability estimates even before water breakthrough, but may require more surveys to be conducted during the history-matching period than assumed in the manuscript. Therefore, it is essential that a detailed cost-benefit analysis be conducted before the usage of crosswell data for history-matching applications. Future work is intended to incorporate other geophysical data sets for reservoir history-matching applications and to examine the framework on real reservoir cases. In addition, several geophysical parameters such as the bulk modulus and Archie's exponents were assumed to be known that may, in reality, be uncertain and should be estimated within the history-matching process. This may be investigated in future research.

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