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Enhanced characterization of reservoir hydrocarbon components using electromagnetic data attributes

Klemens Katterbauer, Santiago Arango, Shuyu Sun, Ibrahim Hoteit

Earth Science & Engineering Program, King Abdullah University of Science and Technology, Saudi Arabia

Advances in electromagnetic imaging techniques have led to the growing utilization of this technology for reservoir monitoring and exploration. These exploit the strong conductivity contrast between the hydrocarbon and water phases and have been used for mapping water front propagation in hydrocarbon reservoirs and enhancing the characterization of the reservoir formation. The conventional approach for the integration of electromagnetic data is to invert the data for saturation properties and then subsequently use the inverted properties as constraints in the history matching process. The non-uniqueness and measurement errors may however make this electromagnetic inversion problem strongly ill-posed, leading to potentially inaccurate saturation profiles. Another limitation of this approach is the uncertainty of Archie's parameters in relating rock conductivity to water saturation, which may vary in the reservoir and are generally poorly known. We present an Ensemble Kalman Filter framework for efficiently integrating electromagnetic data into the history matching process and for simultaneously estimating the Archie's parameters and the variance of the observation error of the electromagnetic data. We apply the proposed framework to a compositional reservoir model. We aim at assessing the relevance of EM data for estimating the different hydrocarbon components of the reservoir. The experimental results demonstrate that the individual hydrocarbon components are generally well matched, with nitrogen exhibiting the strongest improvement. The estimated observation error standard deviations are also within expected levels (between 5 and 10 %), significantly contributing to the robustness of the proposed EM history matching framework. Archie's parameter estimates approximate well the reference profile and assist in the accurate description of the electrical conductivity properties of the reservoir formation, hence leading to estimation accuracy improvements of around 15 %.

Index Terms—History matching, Electromagnetic Data, Observation error covariance estimation, Archie parameter estimation, Ensemble based history matching

I. INTRODUCTION

Recovery of oil and gas has reached new frontiers in the last decades. With the rapid depletion of the world's largest reservoirs, enhancing recovery factors for existing reservoirs has proven critical for optimizing profitability and long term sustainability of the individual corporations. Increasing recovery requires a detailed understanding of the reservoir formation, the pressure levels and increasingly a more comprehensive knowledge of the quantity of the different hydrocarbon components and its PVT dynamics in the reservoir [1]. While black oil model considerations have sufficiently well captured the dynamics for

most reservoirs at the early stages, pressure changes in the reservoir caused by depletion may induce considerable changes in the composition that is caused by chemical reactions. This especially may lead to reservoir dynamics that may significantly deviated from the assumptions made in the black oil model. With the advent of enhanced oil recovery and the injection of gas, chemicals and polymers, history matching for compositional models has grown in importance to track the propagation of these components within the reservoir, evaluate efficiency of the different methods, and enhance production forecasts. Amongst others, Kong et al. [2] presented compositional history matching study to analyze the impact of aquifer intrusion onto a CO₂ gas storage project. A critical factor outlined by Kong et al. was that slight variations in the porosity may significantly affect the CO₂ distribution within the reservoir, thereby suggesting the importance of estimating and studying the individual hydrocarbon components and their behavior. El-Banbi et al. [3] presented a history matching study for a gas-rich condensate reservoir and compared a compositional and modified black oil approach. While the modified black oil model exhibited good history matches for the considered cases, this approach may return significantly poorer results in the case of an aquifer influx. For most modern reservoirs history matching, using a compositional model approach has proved to be essential to adequately capture the reservoir dynamics [4]–[8]. A guideline about when compositional modeling becomes a necessity was presented in Fevang et al. [9]. In a recent article by Gharamti et al. [10] a dual EnKF scheme was presented for the estimation of chemical species in a 2D compositional reservoir model. The authors could demonstrate that the incorporation of chemical composition data may lead to significant enhancements in the permeability estimates, further outlining the benefits of using compositional reservoir simulators and hence compositional information for better history matches.

Electromagnetic (EM) reservoir monitoring has attracted in recent years significant attention for tracking water flooding and aquifer influx for various reservoirs. EM techniques exploit the sharp resistivity contrast between hydrocarbons and brine in order to provide a conductivity mapping of the reservoir. This helps determining flow propagation paths and highly water saturated areas, as well as areas with significant

remains of hydrocarbons. EM imaging techniques have successfully been employed by Marsala et al. [11] in collaboration with Schlumberger, where Saudi Aramco performed field tests in the Haradh field for monitoring the movement of injected water flood front and map the water saturation [12]. The Haradh field is an upper Jurassic carbonate field and the test site consisted of three wells in an oil-water contact zone that may have encountered uneven flood-front distributions. The results provided high quality EM data for the interwell regions that were up to a kilometer apart, and could deliver an accurate resistivity profile for the formation. The cross-well EM imaging instrument used for the field study was outlined in more detail in [12]. Initial studies on the usage of cross-well EM imaging were presented in [13]–[15], focusing on the sensitivity of the EM signals to the reservoir formation parameters and different setups for the cross well imaging. Recently, there has been progress towards further utilizing EM technology for borehole-to-surface EM imaging with Colombo et al. [16] presenting a study for the detection and evolution of the waterfront position and investigating the sensitivity of the modeled EM fields towards the fluid fronts. The study was preceded by a pilot test study by Marsala et al. [17], [18] in which a EM borehole-to-surface survey was used to achieve better reservoir characterization. These developments outlined the growing usage of EM tomography for interwell imaging and complementing gravimetric and seismic technologies whose fluid discrimination ability is considerably less than those of EM techniques [19], [20]. Extensive research was further carried in the EM inversion for single boreholes outlining the necessity to model the salt concentration differences close to the wellbore [21]–[24].

Relating electrical conductivity changes to the dynamics in the reservoir has proven to be significantly challenge in particular for carbonate reservoir formations [25]–[27]. While Archie's Law has been the standard relationship in the industry for decades, research [28]–[33] has shown that its parameters may significantly vary for different formations and rock types and hence need to be calibrated or estimated. Conventionally, resistivity logging tools and core samples are employed to determine saturation and porosity levels and estimate using other well log data the Archie's parameters. While this typically provides a good representation of the rock-conductivity relationship, it may considerably misrepresent the areas

farther away from the wells [34]. Hamada et al. [27], [34], [35] presented a laboratory study for retrieving Archie's parameter and its uncertainty on 29 natural carbonate reservoir core plugs at reservoir conditions. The results of the authors suggest that the Archie's parameters have the strongest influence on calculating the water saturation and initial oil in place from the retrieved resistivity parameters. Using three different techniques, conventional Archie's parameter techniques, core Archie's parameter estimation technique and a three-dimensional technique, the resulting profiles exhibited significantly differing water saturation values that were attributed to the uncertainty levels in the determination of Archie's parameters. Talabani et al. [36] investigated the validity of Archie's equation for carbonate rock formations and concluded that the so called cementation factor m in Archie's equation is influenced by multiple factors, and may significantly differ for complex pore systems. Maute [37] outlined a data-analysis method for obtaining optimal Archie's parameter with reduced uncertainty for the general formation, outlining the challenges and variation in the parameters for a general rock reservoir formation. The effect of the uncertainties in the rock-conductivity parameters was addressed in [38] where the authors proposed approaches to take into account the propagated uncertainties and its importance in properly analyzing the petrophysical properties of the underlying rock formation.

Although several models for relating conductivity of the rock formations to water saturation and porosity have been proposed [39]–[43], none of them has been able to represent various rock formations in a reservoir and all have exhibited high uncertainties in their model parameters [27], making Archie's law the main petrophysical relationship for relating reservoir parameters to the electrical rock conductivity. The conclusions have however outlined the importance of estimating the parameters for different sections of the reservoir to deliver more accurate resistivity-saturation relationships [27], [34].

A different challenge for relating electrical conductivity maps to history matching methods is the spatially varying observational errors that may considerably affect the estimation quality of the reservoir parameters, potentially leading to considerable misestimates [20], [44], [45]. Estimating the observational error variances has gained significant attraction in the last years. Desroziers et al. [46] provided a diagnostic

technique for the analysis of estimation errors in the observation space for data assimilation problems, and discussed a procedure to refine estimates for the observation error covariance matrix. Ueno et al. [47], [48] presented an iterative algorithm for the estimation of the observation noise covariance matrix in the framework of ensemble based data assimilation schemes, such as the Ensemble Kalman Filter (EnKF). Using an expectation maximization approach, the authors could demonstrate fast convergence for even a large number of parameters with a coupled atmosphere-ocean model.

We present a framework for the efficient incorporation of EM data, together with well production data, for enhancing history matching and reservoir characterization in carbonate reservoirs using an EnKF and a compositional reservoir model. Full field Archie's parameters were jointly estimated with the porosity, permeability, and dynamic reservoir parameters using the EnKF. We also follow the approach of [47] to estimate the observation error variances. We focus our analysis on the impact of the EM data on the recovery of the individual hydrocarbon components. The work differs both in terms of focus and technique from previously conducted studies [49]–[52]. We assumed that Archie's parameters are uncertain, spatially heterogeneous, estimated within the history matching process, and investigated the impact of EM data on history matching the individual hydrocarbon components, which has not been investigated previously. The method demonstrates on a realistic carbonate reservoir the opportunities and challenges of incorporating EM data for enhancing reservoir history matching and determining accurate concentration levels of the individual hydrocarbon components in the reservoir. The estimates for permeability and porosity were around 20 % better as compared to history matching only production data. The estimation of the full field Archie's parameter displayed good performance in determining the spatial heterogeneity of these parameters and led to a more accurate reservoir to rock electrical conductivity representation.

II. METHODOLOGY

The framework integrates the compositional reservoir simulator E300 [53] with an Ensemble based Kalman filter and incorporate EM and production data for reservoir history matching, forecasting and quantification

of the uncertainty levels in the estimated reservoir fields. A flowchart representation of the framework is presented in Figure 1. The framework couples a compositional reservoir simulator to an EM survey module that subsequently returns both the EM data and the estimation observation error covariance matrix to the EnKF module, which then estimates both dynamic and static reservoir parameters based on incoming data.

II.1. RESERVOIR SIMULATOR

For reservoir modeling we used the compositional reservoir simulator Eclipse E300 together with a brine tracking conservation equation [53]. Compositional modeling avoids the introduction of pseudo-components as used in black oil models and conserves the mass of the individual hydrocarbon components that may be in gaseous as well as liquid form [54]. The modeling approach therefore takes into account the effects of different phase compositions and the different pressure levels on the individual components, where the exchange mechanism between the various hydrocarbon components is based upon an Equation of State (EOS) model. The corresponding mass balances for the hydrocarbon components is given by

$$\frac{\partial}{\partial t} \left[\phi (c_{kg} \rho_g S_g + c_{ko} \rho_o S_o) \right] = -\nabla \cdot (c_{kg} \rho_g U_g + c_{ko} \rho_o U_o), \quad (1)$$

where c_{kg} and c_{ko} are the mass fractions of the component k in the gas and oil phase, fulfilling

$$\sum_{k=1}^{N_c} c_{kg} = 1, \text{ and } \sum_{k=1}^{N_c} c_{ko} = 1, \quad (2)$$

and the fluid flow velocities for each phase are given by

$$U_o = -\frac{kk_{ro}}{\mu_o} \nabla P_o, \text{ and } U_g = -\frac{kk_{rg}}{\mu_g} \nabla P_g. \quad (3)$$

The Peng Robinson Equation of State (EOS) is used for all components for determining the pressure, temperature and composition dependent density, and equilibrium concentration of the individual components [53], [55]. For determining the viscosity of components, the Lorenz, Bray, Clark correlation was used [56].

The conservation equation for the brine is given by

$$\frac{d}{dt} \left(\frac{S_w c_{salt}}{B_w} \right) = \nabla \cdot \left[\frac{k_{rw}}{B_w \mu_{salt,eff}} (\nabla P_w - \rho_w g \nabla z) \right] c_{salt} + q_w c_{salt,q}, \quad (4)$$

where ρ_w is the water density, c_{salt} the salt concentration, $\mu_{salt,eff}$ the effective viscosity of the salt, and k_{rw} the relative permeability of the water phase, q_w the water production rate, $c_{salt,q}$ the salt concentration of the produced or injected water, P_w the water pressure and g the gravity. The system is solved iteratively via a Newton-Raphson method [53].

II.2. ELECTROMAGNETIC SOLVERS

For computing the EM data attribute (electrical conductivity) of the formation, we utilize Archie's relationship for transforming the salt concentration, porosity and water saturation to the formation conductivity [57]. Archie's relationship states that the logarithmic conductivity $\log(\sigma)$ is related linearly to the logarithm of porosity and saturation, and is mathematically formulated as

$$\log(\sigma) = \log(C_w) + n \log(\phi) + m \log(1 - S_g - S_o), \quad (5)$$

with C_w being a scaled water conductivity, ϕ and S_g, S_o the porosity and the gas and water saturation, respectively.

In this study, the parameters m and n are estimated within the history matching process at each individual grid cell as discussed in Section II.3. The parameter n is conventionally called the cementation factor, and m the water saturation exponent. As outlined in the introduction, Archie's parameters are found to be heterogeneous and typically unknown within the reservoir formation, in particular for carbonate reservoirs, and hence have to be estimated [34]. The conductivity for the injected water C_w is given by the IJWC-Equation [58],

$$C_w = \left[\left(123 \times 10^{-4} + \frac{36475}{10c_s^{0.955}} \right) \frac{82}{1.8T + 39} \right]^{-1}, \quad (6)$$

with c_s being the salt concentration (in ppm) and T the temperature (in $^{\circ}\text{C}$) in the formation.

II.3. HISTORY MATCHING METHODS

For history matching we have used the EnKF. The state-space formulation for the reservoir history matching problem is given by

$$x_{k+1} = M_k(x_k) + \eta_k, \quad (7)$$

$$y_k = h_k(x_k) + \epsilon_k, \quad (8)$$

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

II.3.1. EnKF

The EnKF has in recent years gained considerable attraction for large scale history matching applications in which a larger number of parameters (such as entire permeability and porosity fields) need to be estimated [59]. The EnKF follows the Kalman Filtering implementation in which covariance matrices are approximated by sample covariances estimated from an ensemble, generally assuming that the ensemble members are Gaussian distributed. These assumptions allow the EnKF to advance an approximation of the probability density functions of the state by simply advancing each member of the ensemble in time, making the EnKF computationally very attractive. Despite the Gaussian assumption and the updates being only based on means and covariances, the EnKF has shown to work remarkably well in many studies [19], [20], [59]–[61] and was therefore selected for this history matching study.

In order to achieve efficient computation and to handle eventual nonlinear observations, we have used an observation matrix-free implementation of the EnKF. Let N_e be the ensemble size and $X_k = [x_{1,k}, \dots, x_{N_e,k}]$

the state ensemble matrix at the k -th filtering step, with $x_{i,k}$ denoting the i -th ensemble member. The EnKF operates in two steps:

- A forecast step to integrate the analysis ensemble $X^a = [x_i^a]$ forward in time to obtain the forecast ensemble $X^f = [x_i^f]$ from which the first two moments of the forecast distribution are estimated.
- An analysis step to update the forecasted ensemble with incoming data using the Kalman filter analysis step before proceeding to a new forecast cycle.

More explicitly, define the scaled covariance anomaly

$$A_k = X_k^f - \frac{1}{N_e} \left(\sum_{i=1}^{N_e} x_{i,k}^f \right) e_{1 \times N_e}, \quad (9)$$

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

$$[H_k]_{:,i} = h_k(x_{i,k}^f) - \frac{1}{N_e} \sum_{j=1}^{N_e} h_k(x_{j,k}^f), \quad (10)$$

the observation matrix with $h_k(x_{i,k}^f)$ the observation prediction of the i -th ensemble member $x_{i,k}^f$. Then for the data matrix D_k , with the columns containing the observation perturbed with noise sampled from the observational error covariance matrix R_k the EnKF update step can be written as:

$$X_k^a = X_k^f + \frac{1}{N_e - 1} A_k H_k^T \left(\frac{1}{N_e - 1} H_k H_k^T + R_k \right)^{-1} (D_k - h_k(X_k^f)). \quad (11)$$

The EnKF therefore updates each ensemble independently in such a way that the resulting sample mean and covariance of the updated ensemble exactly matches the Kalman filter analysis and associated error covariance. For further details about the EnKF, the reader may refer to the review articles of Aanonsen et al. [59] and Luo et al. [61].

II.3.2. Observation error variance estimation

Determining the observation errors for EM techniques is challenging as observation error noise levels may

considerably differ for reservoirs and setup environments and therefore needs to be calibrated for each application. Error observation estimation techniques are typically based on a common statistic referred to as innovation, which is the difference between the observation and the forecasted state [48]. For ensemble based methods and nonlinear models, an extended Maximum Likelihood (ML) approach for error observation estimation was presented by Ueno et al. [47]. ML determines the set of parameters that maximizes a given likelihood distribution, thereby measuring the quality of matching the observations. Maximum Likelihood estimation algorithms typically employ an iterative procedure to sequentially update the parameters until convergence is reached. For the observation error estimation we have followed the procedure presented in Ueno et al. [47], [48]. Throughout the presentation we assume that the observation error covariance matrix is diagonal and constant in time, i.e.

$$R = \begin{pmatrix} r_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & r_n \end{pmatrix} = \text{diag}(r_1, \dots, r_n) = \text{diag}(r_i). \quad (12)$$

While the observation error covariance matrix may be changing in time and be non-diagonal, the diagonal assumption and stationarity is in general a good enough approximation and ensures stable estimation results. Then the optimal diagonal elements r_i (representing the variances of EM observation errors for the i -th grid cell) that maximize the log-likelihood are obtained using the following procedure. Given initial variances $r_i^0 > 0$, the posterior probability for the ensemble members at the k -th iteration step is computed as

$$\gamma_l^{(k)} = \frac{\Gamma(y, h(x_l^f), \text{diag}(r_i^{(k)}))}{\sum_{j=1}^N \Gamma(y, h(x_j^f), \text{diag}(r_i^{(k)}))}, \quad l = 1, \dots, N, \quad (13)$$

where Γ is the Gaussian distribution given by

$$\Gamma(y, h, R) = \frac{1}{(2\pi)^{\dim(y)/2}} \frac{1}{|R|^{1/2}} \exp\left[-\frac{1}{2}(y-h)^T R^{-1}(y-h)\right]. \quad (14)$$

The updated observation error variances are then obtained for each ensemble member via

$$r_i^{(k+1)} = \sum_{j=1}^N \gamma_j^{(k)} \left(y_i - h_i(x_j^f) \right)^2, \quad (15)$$

where y_i and $h_i(x_j^f)$ are the i -th elements of the observed and simulated EM data. The iteration is terminated as soon as the stopping criteria, for specified tolerance levels θ and ρ ,

$$L(r^{(k+1)}) - L(r^{(k)}) < \theta |L(r^{(k)})|, \text{ and } \|r^{(k+1)} - r^{(k)}\| < \delta \|r^{(k)}\|, \quad (16)$$

are both met, where the log-likelihood L is defined as

$$L(R) = \log \left(\frac{1}{N} \sum_{j=1}^N \Gamma(y, h(x_j^f), R) \right). \quad (17)$$

The stopping criteria (16) require that the likelihood function value and the estimated parameters between two successive update steps change only marginally, representing a typical local convergence criterion. For a more detailed description of the method, the reader may refer to [47].

III. NUMERICAL EXPERIMENTS AND RESULTS

In this section, we present the experimental setup, investigate the effect of the integration of EM data on the history matching quality of the individual hydrocarbon components, and analyze the estimated Archie's parameters and the EM observation error variances for a realistic 3D synthetic compositional reservoir.

III.1. EXPERIMENTAL SETUP

The studied reservoir represents an anticlinal structure and is 10,000 ft in length, 11,000 ft in width and located at a depth of 7,500 ft (top of the reservoir). The thickness of the reservoir is around 400 ft and the reservoir rock consists of a Jurassic Arab-D limestone [62], [63]. Grid size resolution is around 400 ft in the horizontal plane, and 35 ft in the vertical direction, using a 24 x 25 x 12 grid. The permeability tensor was assumed to be diagonal with $K_{33} = K_{22} / 10 = K_{11} / 10$. The reference permeability and porosity fields were obtained using unconditional simulation incorporating an exponential variogram model with anisotropy axis of 4750 ft in the x direction and 4050 ft in the y -direction, as well as 105 ft in the vertical direction. The reference permeability ranges between 20 and 3,000 mD and the reference porosity between 1 and 49

percent as shown in Figure 2. The reference permeability and porosity fields were then sampled at all wells in order to determine the parameters of an exponential variogram model from which the EnKF initial ensemble is generated, using conditional simulation [64].

The well pattern, outlined in Figure 3, represents an adapted 5P2I pattern, implying that there are two injectors in the center of the domain surrounded by 5 producer wells. The initial pressure in the reservoir was set to 3787 psi and the producing wells have a target rate of 80,000 STB of liquid per day, with an equivalent amount of water being injected into the reservoir to maintain pressure levels. The target rate is for all producing wells. The salt concentration of the brine in the reservoir was assumed to be around 300,000 ppm (105 lbm/STB) and sea water was injected with a salt concentration of around 30,000 ppm (10 lbm/STB) [22], [23], [65], [66]. The relative permeability curves for the oil and water phases as well as the gas and oil phases in the presence of connate water are shown in Figure 4. The components CO_2 , N_2 , C_1 , C_2 , C_3 , IC_4 , NC_4 , IC_5 , NC_5 , C_6 and C_{7+} were explicitly modeled, with C_{7+} representing a component consisting of all hydrocarbon components with more than 7 carbon atoms.

The reference parameter fields for the Archie's parameters m and n were generated using unconditional simulation based again on an exponential variogram model with anisotropy axis of 6,500 ft in the x -direction, and 6,200 ft in the y -direction, and are shown in Figure 5 [34]. The parameter values range between 1.6 and 2.4, ranges that are typically encountered for carbonate reservoirs [27], [34], [36]. Sampling the parameters at the six wells, conditional simulation was then utilized based on an exponential variogram model to generate the initial ensemble of Archie's parameters. The salt concentration evolution for different times is presented in Figure 7. Starting from 2008, the field was then history matched in 2011 and 2014 and forecasted until 2020 to retrieve estimates for production, oil recovery and water saturation levels. Borehole-to-surface surveys were conducted in 2008, 2011 and 2014 and were transformed into electrical conductivity of the formation. Measurement observation errors of the electrical conductivity field are assumed to be Gaussian distributed with mean zero but unknown variances and are latter estimated during the history matching process as outlined in Section II.3.2. The observation error standard deviations

of the EM data attributes were assumed to be around 8 %, which is in agreement with the magnitude encountered in real field applications [18], [67]. The initial observation error standard deviation estimates were sampled randomly from the interval 3 % to 12 %. The realistic 3D reservoir is then employed in history matching experiments to forecast different production parameters, in addition to provide estimates for the pressure, water, oil and gas saturation levels, incorporating both production and EM data attributes. For the production observations the bottom hole pressure (BHP) for all producer wells and the total field production per day were matched. For the BHP observation error rates of 20 psi were assumed and the field production is supposed to have an error rate of around 3 %, based on the specified target rate. The ensemble size is 55 members, which allowed maintaining matching quality with reasonable computational cost. Computational time for a full history matching was around 5 hours and 40 minutes on a Dell T7910 workstation. In the forthcoming study, BASE denotes the experiment where only production data are history matched and EMHM the experiment where the EM data attributes are history matched. Matching performances were evaluated by comparing the Root-Mean Squared Errors (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (d_i^{ref} - d_i^{est})^2}{N}} \quad (18)$$

for the individual cases and each reservoir parameter. In Eq. (18) d_i^{ref} is the i-th component of the reference field, and d_i^{est} is its corresponding estimate as resulting from the EnKF ensemble mean estimate. We have also monitored the spread of the ensemble as an indicator of the uncertainties around the filter estimates [59].

III.2. RESERVOIR CHARACTERIZATION USING EM DATA

In this section, we will present an analysis of the history matching results, incorporating EM data, and investigate its performance with respect to matching and forecasting of the hydrocarbon components. This is followed by a study of the recovery of the permeability and porosity fields, the Archie's parameters, and the estimated EM observation error variances.

III.2.1. History Matching Results

Incorporating EM data for history matching and reservoir characterization is shown to provide valuable information in enhancing tracking of the injected water front, exploiting thereby the sharp conductivity contrast between the water and hydrocarbon phases. This would provide the reservoir engineers an important understanding of the areas penetrated, or not, by the injected water. In the latter case a new well may be drilled to recover these hydrocarbon quantities, depending on its economic feasibility. First, the field gas in place in liquid form is shown in Figure 8, which represents the amount of gas dissolved in oil at reservoir conditions. This is an important parameter for the development of the field, in particular with respect to the amount of gas that has to be processed at the surface. Comparing the BASE results versus EMHM clearly outlines the enhanced estimates of the dissolved gas within the reservoir from the incorporation of EM data, avoiding in particular the underestimation of the amount of gas. When only production data are history matched, the estimate may significantly deviate over the considered time horizon, leading to a considerable underestimation of the solution gas by a dozen million standard cubic feet of gas. A similar conclusion can be deduced for the field water cut that is presented in Figure 9. The incorporation of EM data leads to a considerably better estimate of it that can be deduced from the improved tracking of the water fronts within the reservoir.

Figure 10 and Figure 11 present the hydrocarbon molar production rates for C_3 and NC_5 history matched with BASE and EMHM. Similar to the solution gas, the incorporation of EM data considerably enhances the ability to track the production rates, while reducing the spread between the individual ensemble members while aligning them closer to the reference solution. The performance improvement is further well reflected in Figure 12 showing a comparison of the total well oil production for producer P05 as it results from the history matching with (EMHM) and without (BASE) the incorporation of EM data. The total well oil production of producer P05 reaches around 45 million STB in the reference case, and this behavior is well matched when EM data are incorporated. In the case when solely production data are history matched, a 2 million STB higher output is estimated than actually taking place with the individual

ensemble members returning significantly differing estimates. Finally, the gas production rate for producer P01 is shown in Figure 13 and the water to gas ratio for producer P05 in Figure 14. These clearly demonstrate the considerable matching improvements that result from incorporating EM data for enhancing water front tracking.

Further presented in Figure 15 are the estimated and reference final saturation levels for the oil and water phases. A comparison between the final saturations of the reference field and the estimated field exhibits a strong correspondence to each other, with only the areas surrounding the injection wells exhibiting slightly differing layers. The reason for the slightly differing saturation levels around the injector wells in the uppermost layer of the reservoir is likely due to the tight vertical spacing of the reservoir, which leads to the saturation levels in the uppermost layer being compensated by slightly higher saturation levels in the second highest layer.

For comparative purposes we present in Figure 16 the permeability and porosity estimates when incorporating EM data and for the BASE experiment. The BASE estimates exhibit a rather homogeneous profile that is considerably different from the reference fields as shown in Figure 2. This indicates that the sparse well data are not capable of improving the reservoir characterization as compared to the estimates resulting from EMHM. The incorporation of EM data leads indeed to more refined estimates and a heterogeneous profile that is in better agreement with the reference fields. This is further confirmed by comparing the relative RMSE for the porosity and permeability estimates as shown in Figure 17. While the RMSE for both the permeability and porosity estimates considerably decrease after each update step incorporating EM data, the RMSE for the BASE case remains almost flat and does not encounter almost no further significant improvement. This is consistent with the results presented in Figure 16 and suggests the limitations of sparse well data to recover heterogeneous porosity and permeability fields.

To evaluate the quality of the estimates of Archie's parameters we plot in Figure 18 the EnKF estimates for the parameters m and n , and their corresponding ensemble spread. Comparing the estimates to the reference fields given in Figure 5 one observes coherency between the low and high value regions of the reference

fields and the ensemble estimates. This is further exemplified by the scatter plots of the estimates versus the reference profile (see Figure 18 on the right). An interesting aspect demonstrating the value of the estimation of Archie's parameter is the considerably better estimates for the water saturation exponent m as compared to the porosity exponent n . This might be attributed to the fact that the water saturation changes in the reservoir based on well data enable to better attribute differences in the electrical conductivity to either changing saturation levels or different water saturation exponents, as compared to the static parameter porosity.

To analyze the estimated variances of the measurement errors for the EM data, a histogram of the estimates is presented in Figure 19. The histogram outlines that the estimated standard deviations (square roots of the variances) vary between 3 and 12 %, with the majority of the observation error standard deviations being in the range between 8 and 10 %. This range closely approximates the observation error standard deviation of 8 % assumed in the experiment.

III.2.2. History matching of hydrocarbon components

We summarize in Table 1 and Table 2 the matching improvements for the individual hydrocarbon components and several reservoir parameters as they result from EMHM and compared them with those resulting from the BASE experiment. The history matching enhancement was evaluated as

$$MI = \frac{RMSED_{BASE} - RMSED_{EMHM}}{RMSED_{BASE}} \quad (19)$$

where $RMSED_{BASE}$ and $RMSED_{EMHM}$ are computed via

$$RMSED_X = \sqrt{\frac{\sum_{i=1}^N (d_i^{obs} - d_i^{mean,X})^2}{N}} \quad (20)$$

where $X = BASE, EMHM$, d_i^{obs} and $d_i^{X,mean}$ are the observed data and the ensemble mean estimate for data point i . The expression in equation (19) enables to quantify the reduction in the matching errors achieved via the incorporation of the EM data and all are measured with respect of the reference case. The results in Table 1 indicate significant improvements in matching production from the inclusion of EM data,

outlining the benefits the improved depth imaging has on refining the characterization of the reservoir and enhancing reservoir history matches. In particular, the sparse well data information provides only limited improvements and leads to smooth profile estimates. The integration of EM data partially overcomes this challenge, succeeding to maintain a spatially more heterogeneous profile for all the ensemble members. In order to determine which hydrocarbon components are best recovered and history matched, we further show in Table 2 the matching improvements of the molar production rates at producer well P01. Similar conclusions can be drawn also for the other wells. The results indicate that the molar production rates for all components are well matched and recovered, with the component nitrogen (N_2) exhibiting a slightly stronger improvement as compared to the other hydrocarbon components, followed by the component C_1 . The main reason for this slightly stronger improvement is that Nitrogen has amongst the lowest critical pressures and the lowest critical temperatures, in addition to the lowest critical viscosity. This means that Nitrogen may therefore undergo phase changes more rapidly, leading to rapid changes in the saturation levels that are emphasized in the history matching process when incorporating EM data. Finally, a histogram representation of the matching improvements for parameters were investigated in Figure 20, showing that a majority of the parameters experiences reductions in the RMSE by more than 50% in EMHM. These confirm the considerable improvement obtained from incorporating EM data as discussed above.

IV. DISCUSSION AND CONCLUSIONS

Determining the dynamics of the individual hydrocarbon components within the reservoir has become a necessity with the growing utilization of enhanced oil recovery techniques and moving beyond the black oil treatment. We have presented an EnKF based reservoir history matching study for using EM data to estimate the components of a compositional reservoir model. We have demonstrated the possibility of estimating the parameter of Archie's model used to relate the reservoir formation to the EM data attributes as part of the history matching process. We have further applied an efficient online technique to estimate

the EM observation error variances at the individual grid cells. The results indicate that the incorporation of EM data result in a considerable improvement in characterizing and forecasting the reservoir formation even when the Archie's parameters and the EM variance error are only poorly known. Furthermore, the simulations suggest that nitrogen benefitted most from the incorporation of EM data as compared to other hydrocarbon components. The estimates for Archie's parameters were rather robust, showing a significantly better matching for the water saturation exponent m as compared to the porosity factor n . Finally, the standard deviation estimates of the EM observation errors closely approximated the assumed standard observation of 8 %.

The reported very promising results were obtained with pseudo-data extracted from model simulations, which means that all fitted data are consistent by design in term of the assumed physics in the model. This in particular implies that the different data sets should not compete against each other during the history matching process, especially when an efficient history matching method like the EnKF is used. In real field settings, incomplete understanding of the physical relations between the model and the data may sometimes limit the simultaneous fit to all fitted data. One should also not neglect the challenge due to poor data quality in certain situations, and hence would require some pre-processing to ensure consistency. One should therefore not expect to obtain perfect joint fit to all data in real work applications, and should instead try to balance between the fit of the various data sets and their representativeness in the model. Another aspect that differentiates the proposed approach in the article is in the usage of general EM field data that enables to understand potential fluid propagation channels that goes beyond the usual coverage of well data, which provide only information around the well location.

Future work will address the performance of EM data for other types of reservoirs when being used for history matching. Furthermore, a more thorough study on the correlation between Archie's parameters and the porosity of the carbonate formation may be conducted in future research.

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<i>Matching enhancement (%)</i>	
Parameter	EMHM
Well Water Gas Ratio (P02)	65.53
Total Well Water Cut (P05)	59.20
Total Well Water Injection (I01)	49.55
Average Well Pressure (P04)	54.51
Total Well Gas Production (P03)	50.57
Well Water Production Rate (P03)	74.63
Well Volume Production Rate (P02)	66.51
Field Gas Production Rate	73.53
Total Field Water Production	62.43
Field Water In Place	87.90
Field Oil In Place	68.59

Table 1: Matching improvements for different reservoir parameters. The improvements were computed as reductions in the RMSE normalized by the RMSE of the BASE experiment (history matching production data only).

<i>Matching enhancement – Hydrocarbon components (%)</i>	
Parameter	EMHM
CO ₂ molar production rate (P01)	65.18
N ₂ molar production rate (P01)	67.54
C ₁ molar production rate (P01)	66.14
C ₂ molar production rate (P01)	65.15
C ₃ molar production rate (P01)	65.05
IC ₄ molar production rate (P01)	65.03
NC ₄ molar production rate (P01)	65.02
IC ₅ molar production rate (P01)	65.02
NC ₅ molar production rate (P01)	65.02
C ₆ molar production rate (P01)	65.00
C ₇₊ molar production rate (P01)	64.94

Table 2: Matching improvements for different hydrocarbon components at producer well P01. The improvements were computed as reductions in the RMSE normalized by the RMSE of the BASE experiment (history matching production data only).

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

Figure 2: Reference porosity (left) and permeability (right) fields of the formation.

Figure 3: Reservoir Structure and well pattern.

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

Figure 5: Reference parameter fields for the Archie parameters n (left) and m (right).

Figure 6: Flowchart of the experimental study.

Figure 7: Salt concentration evolution within the reservoir for different times given in lbm/STB.

Figure 8: Field Gas In Place (FGIPL). The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 9: Field Water Cut (FWCT). The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 10: Hydrocarbon Molar Production Rate for C_3 component for producer well P05. The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

EMHM

BASE

Figure 11: Hydrocarbon Molar Production Rate for NC_5 component for producer well P04. The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 12: Well oil production for producer well P05. The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 13: Well gas production rate for producer well P01. The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 14: Total well water gas ratio for producer well P04. The red line represents the reference observation, the gray lines the individual ensemble estimates, the blue line the ensemble mean estimate and the cyan lines the P10 and P90 estimates. The BASE case is using only production data.

Figure 15: Final oil and water saturations for the reference and estimated (average) case.

Figure 16: Comparison of permeability and porosity estimates (averages) incorporating EM data and base case.

Figure 17: Relative RMSE decrease for permeability and porosity for the history matching update steps comparing.

Figure 18: Comparison of estimates (average) for Archie's parameters and scatter plots comparing the initial (blue) and final (red) estimates to the reference field. The black line indicates the identity line.

Figure 19: Histogram of the estimates of the EM error standard deviation.

Figure 20: Histogram of matching improvements considering all parameters.

Highlights

- Performance of the usage of electromagnetic data for reservoir monitoring and history matching purposes
- Reduction in the uncertainty for the history matches using electromagnetic data
- Estimation of noise levels of the electromagnetic data
- Enhanced characterization of the reservoir formation, in particular the permeability and porosity fields
- Better characterization of hydrocarbon components when jointly used with well data. Caused by the better tracking of water fronts and hence hydrocarbon characterization of the reservoir.