Adaptive local parameterization of facies proportions for the history matching of production and time lapse saturation data

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1 Introduction

One of the main challenges in reservoir engineering is to reduce the uncertainties in production forecasting. To that purpose, several techniques have been developed to help building permeability and porosity fields, which satisfy the available static data (facies observation, petrophysical properties at wells, etc) and provide a simulated flow response that fits the observed dynamic data such as water cut data, oil rates at wells or time lapse seismic data.

Spatial distributions of facies and petrophysical properties are often modeled using random functions with statistical properties (mean, variance, variogram) inferred from the static data. In this context, several parameterization methods have been proposed to update facies and petrophysical property realizations while honoring the statistical model. Among these techniques are the pilot point method [15], the gradual deformation method [6] and the probability perturbation method [1]. These techniques make it possible to investigate the spatial distribution of facies for some given proportions, and have been used for history matching. In the case of facies simulation, facies proportions in the reservoir can have a strong impact on the dynamic behavior. Moreover, spatial trends inferred between the wells may be uncertain and need to be calibrated using various sources of information. This motivated the development of new parameterization methods dedicated to the perturbation of facies proportions and integrated in history matching processes to better match production data. In [12], the truncation thresholds used in the truncated pluri-Gaussian method [9] are modified during the history matching process, leading to the perturbation of the proportion of each facies. In [5], the authors combine the multi-parameter probability perturbation method with a perturbation of local facies proportions, adjusted during the optimization process. Finally, the facies proportion calibration method proposed in [14] consists in modifying locally the average proportion ratio of a group of facies within a larger selection of facies. It has been applied to the history matching of production and 4D seismic data in [16].

When using the truncated Gaussian methods [13, 9], facies proportions correspond to probabilities of occurrence of facies at each location, and can vary spatially in the reservoir. The method proposed in [14] perturbs locally the facies proportions, disregarding the spatial continuity of these proportions. In this paper, we propose a new parameterization technique that preserves the continuity in spatial distributions of facies proportions. It is based on the parameterization of the proportions $(p_i)_{i=1..N}$ of N facies using only $N-1$ parameters $(\rho_j)_{j=1..N-1}$, defined such as facies proportions belong to the space $\{(p_i)_{i=1..N} | \sum_{i=1..N} p_i = 1\}$ for any set of parameters $(\rho_j)_{j=1..N-1}$ (see section 2). A continuous distribution of each of these parameters over the spatial domain leads to a continuous distribution of facies proportions. Other parameterization approaches can be envisioned and will be the subject of forthcoming papers. Several methods can be used to perturb locally the spatial distribution of parameters $(\rho_j)_{j=1..N-1}$. Here, we propose to apply a conditioning by kriging on linear volume averages [8] in order to preserve their spatial continuity (see section 3). This technique can also be combined with a history matching process, modifying iteratively the local average values imposed to the parameters until a satisfactory match is obtained, as proposed for instance in [3, 11, 4] to perturb continuous petrophysical properties. It can be used simultaneously with other parameterization techniques such as the gradual deformation.

Previous studies have shown that the integration of 4D seismic data in the history matching process could improve the match of production data and the reliability of prediction [16]. However, the match can be difficult to obtain and techniques such as gradual deformation may lack efficiency. New parameterization techniques adapted more specifically to 4D seismic data were thus developed for the calibration of continuous petrophysical properties [3, 11, 4]. In this paper, we propose to apply the gradual deformation and the local parameterization of facies proportions for the history matching of production data and saturation data, which are assumed to be derived from 4D seismics (section 4). The identification of the regions for locally perturbing the proportions is based on the analysis of the highest matching residuals for the 4D seismic data as proposed in [3, 4].

2 Parameterization of facies proportions

Let us consider a set of $N \geq 2$ facies with proportions $(p_i)_{i=1..N}$, defined as the probability of occurrence of each facies at a given location and satisfying:

$$p_i \geq 0 \quad \text{and} \quad \sum_{i=1}^{N} p_i = 1. \tag{1}$$

Several parameterizations of these proportions can be used, as the one proposed in [14] involving average proportions ratios between groups of facies. In this paper, we propose to describe the N proportions using only $N-1$ parameters $(\rho_j)_{j=1..N-1}$ defined by

$$p_1 = \prod_{j=1}^{N-1} cos^2(\pi\rho_j), \quad p_i = sin^2(\pi\rho_{i-1}) \prod_{j=i}^{N-1} cos^2(\pi\rho_j) \quad \forall j = 2..N-1, \quad p_N = sin^2(\pi\rho_{N-1}). \tag{2}$$

The parameters $(\rho_j)_{j=1..N-1}$ can be uniquely computed in the interval [0:0.5] applying the following recursive algorithm:

1. $\rho_{N-1} = \frac{1}{\pi} asin\sqrt{p_N}$
2. For all $i = N-2, ..., 1$,
   a) If $\sum_{j=i+2}^{N} p_j < 1$, then $\rho_i = \frac{1}{\pi} asin\sqrt{\frac{p_{i+1}}{\prod_{j=i+1}^{N-1} cos^2(\pi\rho_j)}}$
   b) Otherwise, the choice of ρ_i is arbitrary. It is taken equal to 1/4 here, or equivalently $p_i = \sum_{j=1}^{i-1} p_j$.

As it can be seen, any set of parameters $(\rho_j)_{j=1..N-1}$ within $[0 : 0.5]^{N-1}$ represents an ensemble of facies proportions $(p_i)_{i=1..N}$ satisfying conditions (1).

3 Local transformation of a proportion curve using kriging on linear volume averages

To modify locally the spatial distribution of the parameters described in the previous section, we propose here to use a conditioning by kriging on linear volume averages as described in section 3.1. An example is given in section 3.2.

3.1 Conditioning by kriging on linear volume averages

In this section, a technique used to condition a continuous realization on some local linear volume averages is described. It is based on kriging using point data and linear averages over centered volumes as described in [8] and on conditional kriging as used to constrain continuous realizations to static data [2].

Let $z(u)$ be a continuous attribute function of location vector $u \in A$, A being the domain studied, and Z a continuous stationary random function with mean m and a positive definite covariance function $C(h)$, h being the distance vector, which models the distribution of $z(u)$. Also let $V(u_k)$ be a volume centered in u_k and $d_V(u_k)$ be a secondary random variable equal to the linear volume average of primary variable z over volume $V(u_k)$. Let us assume that the values $z(u_i)$ and the linear volume averages $d(V_j)$ are known for n distinct points u_i, $i = 1..n$, and N volumes $V(u_j)$, $j = 1..N$. Then, an unbiased estimator of Z at location u can be written using these $n + N$ pieces of information as:

$$Z^*(u) = \sum_{i=1}^{n} \lambda_i(u)[Z(u_i) - m] + \sum_{j=1}^{N} \mu_j(u)[D_V(u_j) - m] + m \tag{3}$$

where $Z(u_i)$, $i = 1..n$, are the primary random variable data with mean m and covariance $C(h)$, and $D_V(u_j)$, $j = 1..N$, are the secondary random variable data with mean $m_{D_j} = m$. The weights $\lambda_i(u)$, $i = 1..n$ and $\mu_j(u)$, $j = 1..N$, are determined so as to minimize the error variance and satisfy a linear system involving the point-to-block and block-to-block covariances directly derived from the primary covariance function $C(h)$. More details can be found for instance in [8]. The estimator Z^* honors the values $z(u_i)$ for all $i = 1..n$ and the linear volume averages $d_V(u_j)$ for all $j = 1..N$.

Let us now consider a realization z_s of Z. Let us note d^* the estimator obtained applying equation (3) to the data $z(u_i)$, $i = 1..n$, and $d_V(u_j)$, $j = 1..N$. The same formulation can be applied to the values of z_s at points u_i, $i = 1..n$ and to the simulated average values on $V(u_j)$, $j = 1..N$, resulting in estimator z_s^*. Then, conditional kriging consists of modifying realization z_s so that it honors the measured values and averages:

$$z_c = z_s + (d^* - z_s^*).$$

In this equation, z_c is said to be conditional.

3.2 Local transformation of a proportion curve

Let us consider a 1D example with 3 facies $F1$, $F2$ and $F3$ and 100 cells along direction X. The initial proportions $p_1 = p(F1)$, $p_2 = p(F2)$ and $p_3 = p(F3)$ are plotted on Figure 1-(a). Applying the methodology described in section 2, two parameters are defined on the grid:

$$\rho_2 = \frac{1}{\pi} asin \sqrt{p_3} \text{ and } \rho_1 = \frac{1}{\pi} asin \sqrt{\frac{p_2}{cos(\pi\rho_2)^2}}.$$

Initially, the average value of parameter ρ_2 in the region between the two dashed vertical lines is 0.388. Applying the conditioning technique described in section 3.1, this value is changed to 0.185. The resulting proportions are plotted on Figure 1-(b). They are changed between the vertical lines, but also in the neighborhood of this region due to the correlation length of the variogram used for kriging.

4 History matching of production and time lapse saturation data

Let us now apply the parameterization technique described in the previous sections in a history matching process, considering production and saturation data. The latter are assumed to be derived from 4D seismics.

4.1 Test case description

We consider a 2D horizontal synthetic case with one injection well located at the center of the grid and four production wells located at the corners. The same grid is used for the geological model and the reservoir simulation, with 100 × 100 grid nodes of size 5 m × 5 m. It is populated with three facies F1, F2 and F3. Their proportions are stationary. Each facies is attributed homogeneous permeability and porosity values recapped in Table 1. The truncated Gaussian algorithm [13] is applied to generate a reference facies distribution: a standard Gaussian realization with a stable variogram is truncated according to the facies proportions. The main anisotropy direction of the variogram is defined by an angle of 45° with respect to the X-axis. The horizontal variogram ranges are 120 m and 40 m. The field presented in Figure 2-(a) is considered in the following as the true field. The reservoir is initially saturated with oil and irreducible water. Compressibility and capillary pressure are ignored. The mobility ratio of oil to water is 6.5. Standard quadratic relative permeability curves are used with an irreducible water saturation equal to 0.15 and a residual oil saturation equal to 0.2. A two-phase black-oil simulator is used to simulate the reservoir flow evolution in time. Water is injected during 5 years with an injection rate of 200 sm^3/day, and the production wells have a production rate of 50 sm^3/day. No-flow conditions are imposed at the boundaries. For this reference case, the observed dynamic data are the water cut, bottom hole pressure and surface oil rate at the production wells, the bottom hole pressure at the injector and the water saturation in the reservoir at time $t_1 = 1095$ days (Figure 2(b)).

4.2 History matching process

4.2.1 Description

Let us now apply a history matching process to this synthetic test case, in order to reproduce as best as possible the reference dynamic data while honoring the structural properties of the geological model. The history matching process proposed here integrates simultaneously the geostatistical simulation of the geological model and the fluid-flow simulation. An objective function (OF) is defined that measures the mismatch between the reference data and the corresponding simulated answer provided by the fluid-flow simulator. It is computed using a weighted least square formulation.

The facies realization can be perturbed applying the gradual deformation and the kriging-based approach, either sequentially or simultaneously. The kriging based approach will be applied to parameters ρ_1 and ρ_2 defined by (2), using the same variogram as the one assigned to the facies. The gradual deformation will apply to the standard Gaussian realization simulated using the FFT-MA algorithm [10] and truncated according to the facies proportions [7]: deformation parameters are used to combine several Gaussian White Noises on the whole grid, resulting in a new Gaussian White Noise transformed according to the structural parameters by the FFT-MA algorithm. When applying this method in an assisted history matching process, the deformation parameters are adjusted to obtain the best combination in terms of objective function decrease. If the match is not satisfactory, the process can be repeated, combining the optimal Gaussian White Noise with new ones. Gradual deformation based optimizations thus consist in investigating successive chains of Gaussian white noises and in searching a combination that minimizes the objective function.

The kriging based approach requires to define non-overlapping regions in the reservoir. Here, these regions are defined using the method proposed in [3, 4]. The aim is to identify areas, which should influence the dynamic behavior in the regions of the reservoir where seismic data are badly reproduced. First, the parts of the domain with a mismatch on the saturation higher than a given threshold ε_T are identified. Then, each of these regions is augmented with its influence area, defined by the points located on streamlines arriving to the region.

4.2.2 Results

First, a gradual deformation based optimization chain was performed using two deformation parameters, thus combining three Gaussian White Noises. An optimization algorithm based on gradients computation is applied to minimize the objective function. The results obtained after 21 optimizations are presented on Figure 3, each optimization involving the combination of three independent Gaussian White Noises. As can be seen, the objective function decreases rapidly during ten optimizations before a stagnation during the next optimizations, what appears quite typical of the method. Furthermore, the contribution of the saturation data in the objective function is almost stationary: the method does not seem efficient for these spatial data. Thus, this first step in the history matching process provides rapidly a facies model that reasonably match the data but could still be improved.

Then, we have tried to refine the best model obtained at the end of optimization 12, denoted as 'initial model', modifying locally the facies proportions with the parameterization technique proposed in sections 2 and 3. The corresponding initial facies and saturation distribution at time t_1 are plotted on Figure 2(c) and (d), respectively. Regions were computed considering an error on the saturations higher than $\varepsilon_T = 0.2$ (see Figure 4). Then, a second optimization was performed from the initial model, adjusting the local average values imposed by kriging to parameters ρ_1 and ρ_2 in order to reduce further the objective function. The Gaussian White Noise used to simulate the facies remains unchanged, equal to the one used to simulate the initial model. The maximum number of fluid-flow simulations is 50, the simulations used to compute the gradients being included in this number. The final model, called M(0.2), is presented in Figure 2(e)-(f). As can be seen, the water saturation distribution has become closer to the reference one in some areas, especially

Facies	Proportion	Porosity	Kh (mD)	Kv (mD)
F1	$p_1 = 0.15$	0.2	600	60
F2	$p_2 = 0.25$	0.2	350	35
F3	$p_3 = 0.6$	0.2	50	5

Table 1: Initial proportions and petrophysical properties for each facies.

in the right central part of the domain. This can be explained by the decreased proportion of the less permeable facies $F3$ in this area. To try to minimize further the objective function, one could update the regions from model M(0.2) and again calibrate the parameters average values in the updated regions.

On Figure 6 are plotted the evolution of the objective function with respect to the number of fluid-flow simulations during the 21 gradual deformation based optimizations (the initial model corresponds to "Opt #12") and during the calibration of the facies proportions from the initial model. This second step in the history matching process thus enables a stronger decrease of the objective function for an equivalent computation time compared to the gradual deformation based optimizations. Furthermore, the contribution of the saturation in the objective function has been significantly reduced, without degrading the match on the production data.

5 Conclusions

In this paper, we have proposed a new parameterization for facies proportions. Combined with a kriging on linear volume averages, it makes it possible to perturb smoothly the spatial distributions of facies proportions in some given regions while preserving the spatial continuity of these distributions. This method has been proved to be efficient for the history matching of production and saturation data on a 2D synthetic case: considering regions identified from the mismatch on the saturation data, the objective function was significantly reduced, especially the contribution of the saturation data.

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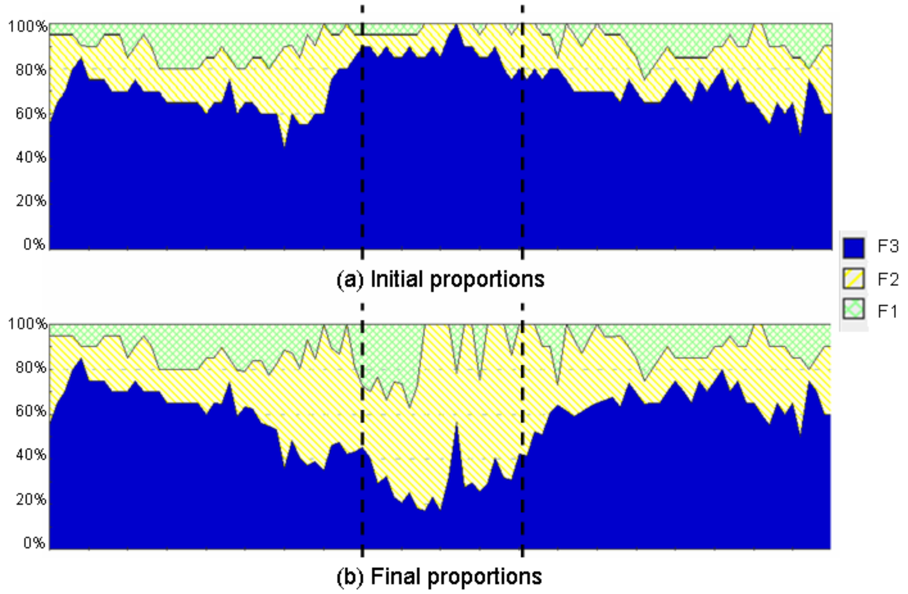

Figure 1: Value of (a) the initial facies proportions and (b) the transformed proportions.

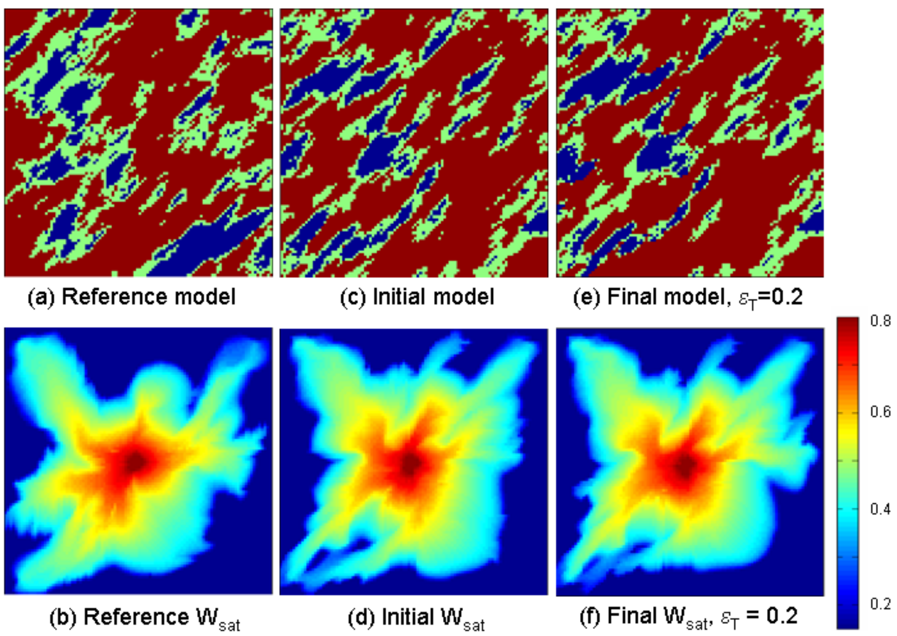

Figure 2: Facies distributions and corresponding water saturation in the reservoir at time t_1 for (a)-(b) the reference model, (c)-(d) the initial model and (e)-(f) model M(0.2) obtained after perturbing the facies proportions with $\varepsilon_T = 0.2$.

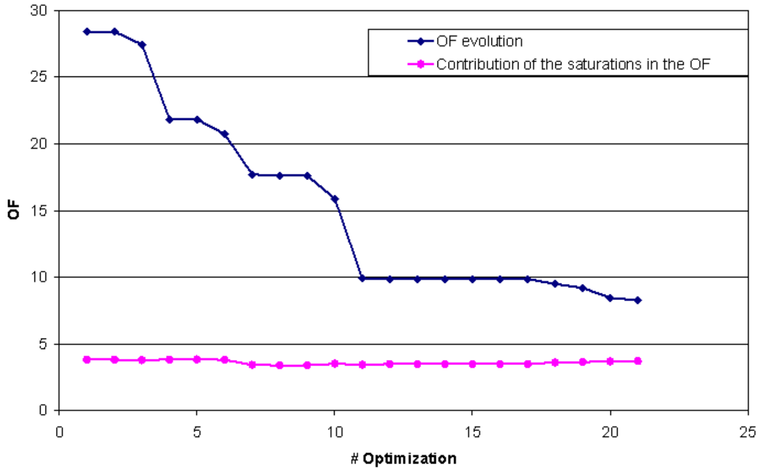

Figure 3: Objective function evolution during the gradual deformation based optimizations.

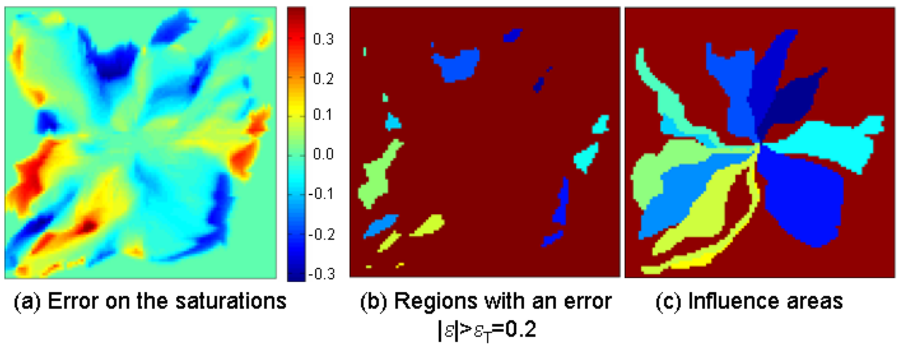

Figure 4: Definition of the regions for locally perturbing the facies proportions.

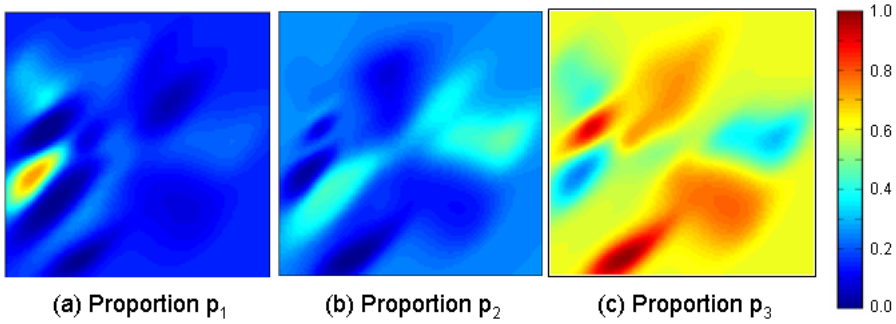

Figure 5: Facies proportions in the reservoir with model M(0.2).

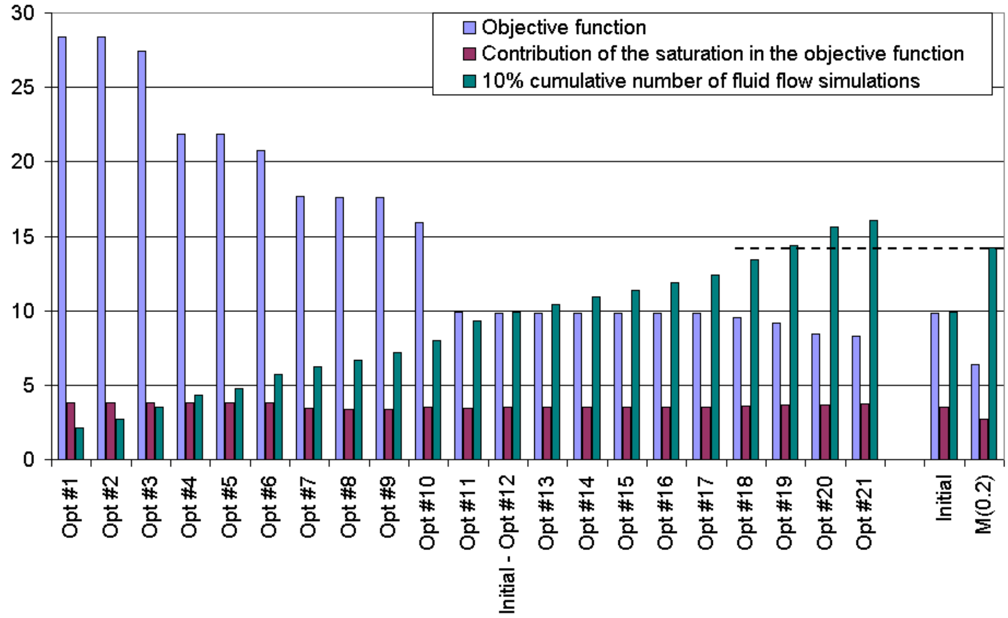

Figure 6: Objective function evolution during the two steps of the history matching process.

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