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A generalization of the local gradual deformation method using domain parameterization

Benjamin Marteau [a,*], Didier Yu Ding [a], Laurent Dumas [b]

[a] IFP énergies nouvelles avenue Bois Préau, Rueil-Malmaison, France
[b] Université de Versailles Saint-Quentin, avenue de Paris, Versailles, France

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ABSTRACT

Reservoir model needs to be constrained by various data, including dynamic production data. Reservoir heterogeneities are usually described using geostatistical approaches. Constraining geological/geostatistical model realizations by dynamic data is generally performed through history matching, which is a complex inversion process and requires a parameterization of the geostatistical realizations for model updating. However, the parameterization techniques are still not very efficient and need to be improved.

In recent years, the local gradual deformation method has been widely used to parameterize geostatistical realizations. The domain deformation technique has also been developed to improve the history matching efficiency. Both methods can smoothly modify model realizations while conserving spatial geostatistical properties. The first one consists in locally combining two or more realizations while the second one allows the optimization process to change the model realization via the variation of the shape of geometrical domains. In this paper, we generalize the local gradual deformation method by adding the possibility to change the geometry of local zones through the domain deformation. This generalization provides a greater flexibility in the definition of the local domains for the local gradual deformation method. In addition, we propose a new way to initialize the realization which guarantees a good initial point for the optimization and potentially improves the efficiency of history matching.

1. Introduction

A reservoir model is built based on both static and dynamic data. Static data represent the data obtained from experiments carried out on cores extracted from wells or measurements of well logs such as porosity or permeability. Dynamic data are generally the well production data such as well pressure and oil rate. The integration of dynamic data in the reservoir model is generally performed through history matching.

Reservoir heterogeneities are described using geological/geostatistical approach. The uncertainty of a model realization is linked to the geological scheme, to the sedimentary concept, to the nature of the reservoir rocks, to their extent, and to their properties. Ignoring the uncertainties in the reservoir lithology would lead to underestimating the complexity of the reservoir between wells, resulting in over- or under-estimating the connected reservoir pore volumes. Integration of dynamic data to constrain the geostatistical realization can reduce greatly model uncertainties. Although reservoir heterogeneities are commonly generated using geostatistical models, random realizations cannot generally match observed dynamic data. To constrain model realizations to reproduce measured dynamic data, an optimization procedure may be applied in an attempt to minimize an objective function. Such history matching methods require a parameterization of the geostatistical model to allow the updating of an initial model realization.

To parameterize the geostatistical model, several methods were introduced. For example, the pilot point method (Marsily et al., 1984), the gradual deformation method (Roggero and Hu, 1998), the domain deformation method (Ding and Roggero, 2010) and the probability perturbation method (Hoffman and Caers, 2003) were all proposed to continuously deform the models. All these methods allow the modification of a geostatistical realization by preserving its spatial variability.

In recent years, the local gradual deformation method has been increasingly used (Roggero et al., 2007; Al-akhdar et al., 2012). In that method, the deformation zones are fixed and cannot be changed during history matching. If these zones are not suitably defined, it is difficult to decrease the objective function for history matching and to find an optimal realization. The choice of deformation zones is a critical point for the successful history matching of geostatistical realizations. In this paper, we propose a generalization of the local gradual deformation method, which can

* Corresponding author. Tel.:+33782635306.
E-mail addresses: benjamin.marteau@ifpen.fr, benjamin.marteau@laposte.net (B. Marteau).

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optimize the deformation zones through the domain deformation technique during a history matching process. This method allows the gradual deformation in varying domains and find more efficiently an optimal geostatistical realization.

Another issue in history matching is the selection of the initial model realization for the local gradual deformation. The batch-work method, which combines locally different realizations according to the matching results on the wells (Reis et al., 2000), is sometimes used to define an initial model. But this method does not always work well, and sometimes gives very bad results. Using the domain deformation technique alone may provide a suitable approach to define a convenient initial model.

In this paper, we will first briefly review the gradual deformation and the domain deformation methods, then present a generalization of the gradual deformation method by combining with the domain deformation technique to modify the shapes and sizes of the domains. We will also show how to get a convenient initial model for history matching by using the domain deformation technique. Examples are presented to show some promising results with the new technique.

2. A generalized local gradual deformation technique

2.1. Gradual deformation method

Some geostatistical methods such as the Fast Fourier Transform Moving Average (FFT-MA) (Le Ravalec et al., 2000) allow us to uncouple uncorrelated random realizations from structured information (mean, variance, correlation length, etc.). With such methods, a model realization M is linked to a standard Gaussian white noise Z by an operator G:

$$M = G(Z) \tag{1}$$

The gradual deformation method (Gervais et al., 2007; Hu, 2002; Roggero and Hu, 1998) consists in combining two or more Gaussian white noises to modify the model realization. More precisely, it uses the fact that if $(Z_0, \ldots, Z_N)$ are $N+1$ independent standard Gaussian white noises and $(a_0, \ldots, a_N)$ are $N+1$ real numbers such that $\sum_i a_i^2 = 1$, then $Z = \sum_i a_i Z_i$ is still a standard Gaussian white noise. Then, if the a_i depend on a set of parameters $\rho = (\rho^1, \ldots, \rho^N)$ that guarantees that for all ρ, $\sum_i a_i^2(\rho) = 1$, we can generate new model realizations for all ρ. Moreover, a continuous variation of the set of parameters ρ gives a continuous variation of the spatial properties of the model realization as illustrated in Fig. 1. For example, if we want to combine two independent Gaussian white noises Z_0 and Z_1, we can introduce a parameter ρ^1 and choose $Z(\rho^1)$ such as

$$Z(\rho^1) = \cos(\rho^1) Z_0 + \sin(\rho^1) Z_1 \tag{2}$$

To combine $N+1$ Gaussian white noises $(Z_0, \ldots, Z_N)$, we introduce N parameters $\rho = (\rho^1, \ldots, \rho^N)$. The gradual deformation is then given by

$$Z = \prod_{i=1}^{N} \cos(\rho^i) Z_0 + \sum_{i=1}^{N-1} \sin(\rho^i) \prod_{k=i+1}^{N} \cos(\rho^k) Z_i + \sin(\rho^N) Z_N \tag{3}$$

For local gradual deformation, we group the model grid cells in zones and locally combine several Gaussian white noises inside these zones. For example, if the model is divided into two zones, then three standard Gaussian white noises are available:

$$Z_0 = \begin{bmatrix} Z_{0,zone_1} \\ Z_{0,zone_2} \end{bmatrix}, \quad Z_1 = \begin{bmatrix} Z_{1,zone_1} \\ Z_{1,zone_2} \end{bmatrix} \quad \text{and} \quad Z_2 = \begin{bmatrix} Z_{2,zone_1} \\ Z_{2,zone_2} \end{bmatrix} \tag{4}$$

we can define $Z(\rho)$ by

$$Z(\rho) = \begin{bmatrix} \cos(\rho^1) Z_{0,zone_1} + \sin(\rho^1) Z_{1,zone_1} \\ \cos(\rho^2) Z_{0,zone_2} + \sin(\rho^2) Z_{2,zone_2} \end{bmatrix} \tag{5}$$

with $\rho = (\rho^1, \rho^2)$. $Z(\rho)$ is still a standard Gaussian white noise and can thus still legitimately be used to generate a model realization through the operator G. In this case, Z_0 and Z_1 are combined in the domain $zone_1$ and Z_0 and Z_2 are combined in the domain $zone_2$. This approach allows us to independently modify realizations in several regions of the model.

2.2. Domains deformation method

The domain deformation method (Ding and Roggero, 2010) has some similarities to the local gradual deformation method. The model is divided into different zones (not necessarily delimited by grid cells) and a standard Gaussian white noise is restrained to each zone. The geostatistical model realization is then modified by deforming the shapes and sizes of the zones. Fig. 2 shows an example of a reservoir model divided into two domains R_1 and R_2. We build the model realization with a standard Gaussian white noise associated to Z_1 inside R_1 and to Z_2 inside R_2. However, the random value is not clearly defined on grid cells that are partially on several domains. Let us consider the grid cell X of Fig. 2 which is not entirely inside any domain. To ensure the model continuity, we choose for this grid cell a combination of the two Gaussian white noises Z_1 and Z_2 as follows:

$$Z_X = a_1 Z_{1,X} + a_2 Z_{2,X} \tag{6}$$

where a_1 and a_2 depend on the shape and the size of the domains, respectively, which can be parameterized. As for the local gradual deformation method, Z is a standard Gaussian white noise if $a_1^2 + a_2^2 = 1$. We can choose, for example, a_i proportional to the proportion of the grid cell inside the domain i.

The new model realization therefore depends on the parameters which define the shapes and sizes of the domains. In general, to limit the number of parameters, we choose simple shapes for the domains that depend only on a small number of parameters. For example, choosing circles with fixed centers allows us to determine each domain with only one parameter: their radius.

This method can be extended to the case of M domains to deform with $N+1$ Gaussian white noises. Let $t_i = (t^1, \ldots, t^q)$ be the set of parameters determining the shape of the domain R_i and $t = (t_1, \ldots, t_M)$ contain all the domain parameters, we can combine the Gaussian white noises

$$Z(X, t) = \sum_{i=0}^{M} a_i(X, t_i) Z_{J(i)}(X) \tag{7}$$

where $a_i(X, t_i)$ depends on the shape of the domain R_i, $J(i) \in [0, \ldots, N]$ is the index of the Gaussian white noise associated to the domain R_i and $J(0) = 0$. The new standard Gaussian white noise is parameterized with t.

The advantage of this parameterization technique compared to the local gradual deformation is that it is not very dependent on the initial domain selections, since their shapes and sizes can be modified. In fact, a bad definition of the zones in the local gradual deformation method could greatly deteriorate the potential diminution of the objective function. This is well illustrated in Fig. 3 which was presented by Ding and Roggero (2010) to compare the potential of the domain deformation method and the gradual deformation method on a history matching problem. In this figure, the pink curve presents the variations of the objective function with the size of the domains, while the blue curve presents the optimal results using the local gradual