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Reducing uncertainty in reservoir parameters combining history matching and conditioned geostatistical realizations

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ABSTRACT

History matching is an iterative process that modifies a reservoir model to reproduce field behavior. Due to the scarcity of data the true distribution of facies, porosity and permeability between widely spaced wells is unknown, resulting in high uncertainty.
As the spatial patterns of permeability and porosity often significantly affect the flow response, evaluating heterogeneity is key in history matching.
This work presents a stochastic method for use in probabilistic and iterative history matching. We select a set of the best geostatistical realizations and reproduce their spatial patterns in subsequent iterations to create a new set of better-matched models. All models, throughout the process, honor well log data and continuity, modeled with the variograms.
This paper uses four approaches: two using a global method and two using a regional method. Both methods improved dynamic history data matching while honoring all well data but each is suited to different times in exploration and production.
We present the global method as a simple tool to improve models. Characterized as an update of the entire reservoir, it is useful when the number of wells and the dynamic history data are scarce. The regional method is more efficient to process large amounts of information, enabling the independent match of dynamic well data, avoiding mismatches with other wells.

1. Introduction

One of the most important activities in the oil industry is forecasting reservoir production. Reservoir models should consider all available data (seismic, well logs, cores etc.) to improve reliability.

Despite the possibility of obtaining a single model that fully respects all information and observed production data, a set of scenarios can be useful to provide alternative forecasts, even if they all reproduce the same history data (Maschio et al., 2010).

Simulated models are calibrated using historical data (known as history matching) to achieve sufficient reliability to perform risk analyses and support decisions.

History matching is an inverse problem, in which we use the known solution (real production data) to find the parameters (permeability and porosity). The global framework of a history matching process is based on minimizing an objective function that quantifies the mismatch between the history data and the simulated data through an iterative process. These parameters can include petrophysical parameters such as porosity, permeability or net-to-gross ratio, and other parameters, such as oil-water contact, rock compressibility and relative permeability.

Heterogeneity is responsible for the location of high permeability channels, barriers and other events that affect flux, pressure, the time it takes water to reach the well and other data used to evaluate reservoir behavior. Therefore, reducing uncertainty in the spatial distribution of petrophysical properties improves accuracy in history matching.

In traditional history matching, mismatched regions are modified using a multiplier in geostatistical parameters (porosity, permeability etc.), until an acceptable value is reached (Mattax and Dalton, 2000; Miliken et al., 2001). This method can produce good results when matching production data. However, it does not account for any geological, geophysical or petrophysical knowledge of the reservoir, and usually creates models without structural consistency. So, even if the model does respect history data, long-term forecasting is likely to be inaccurate.

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The main challenge when modeling a reservoir is to respect all well data and geological analyses, while reproducing observed production data. The complexity of history matching lies in the number of variables that the model must honor and the multiple solutions that create the same answer (inverse problem).

Geostatistics has gained special attention in recent years as a tool that honors all well data, reservoir structure and reservoir continuity. It has the advantage of creating a set of equiprobable images, allowing the analysis of different solutions to the inverse problem. For this reason, various studies have integrated geostatistics with history matching.

Geostatistical history matching procedures are usually based on stochastic simulations to perturb parameters within the iterative loop procedure. Following are methods used in history matching procedures summarizing the advantages and disadvantages.

Gradual deformation uses a linear combination of independent realizations (Hu, 2000; Roggero and Hu, 1998) to generate new and improved models. The disadvantages are that it is only applicable in Gaussian fields; it must be near the solution to converge rapidly, integration of secondary information is difficult, and it may not keep the structure in models with high continuity such as channels. However, the method is quite simple, flexible and can be used globally or regionally.

To explore the application of this method in non-Gaussian fields, Hu et al., 2001 used the same principle to locally perturb three facies using Sequential Indicator Simulation (SIS). They concluded that the method was applicable in a wide range of situations, producing good results.

There are two types of perturbation: global and local. Global perturbation is of the entire reservoir at once, based on the average mismatch of all wells. Local (or regional) perturbations depend on individual well mismatches and are performed within the influence areas of each well. Global perturbation is easy to implement but the convergence for all wells is difficult, as it disregards the individual speed of convergence of each well. Local perturbation requires defined areas of influence local for each producer or injector well.

Gervais et al. (2007) compared the gradual deformation method when applied globally or regionally. He concluded, when using the regional method, that maximum speed of convergence is higher and the minimum, lower, for the objective function. They used a Voronoi polygon for each well to divide the reservoir into areas of influence for different wells and grouped them according to (1) Voronoi polygons with the same match quality, (2) polygons in the same streamlines.

Mata-Lima (2008a,b) suggested another method to perturb geostatistical realizations, using Direct Sequential Co-simulation (Soares, 2001) to constrain the pattern of a reservoir image.

Co-simulation was first used to integrate secondary information into the data that one wanted to simulate. Starting by integrating seismic data to achieve porosity, and integrating porosity to simulate permeability. In the work developed by Mata-Lima, co-simulation was used to guarantee that, once the user selected an image, the subsequent iterations would respect that image pattern. The selected image was used as a secondary variable in co-simulation.

Mata-Lima (2008a) proposed and tested an algorithm in a simple reservoir, composed of a single layer of grid blocks. The square grid blocks had a uniform thickness of 10 m. All tests were done constant porosity, with only the permeability field characterization missing. The reservoir was composed of three wells, one injector and two producers.

He concluded that the proposed algorithm preserved the variogram and histogram of permeability since the co-simulation uses a Markov approach. This approach requires only the variogram of the original variable and the correlation coefficient between primary and secondary variables to produce new stochastic realizations.

Despite the simplicity of the case, the promising results prompt further testing of the methodology in more complex cases. Some other case studies have used co-simulation to history match a reservoir model (Caeiro et al., 2013, 2014). tested co-simulation in a 2D anisotropic synthetic case improving the consistency of the good results achieved in Mata-Lima (2008a,b).

In this work, we implement the global outline, set out in previous works, in more complex and realistic situations. We reduce the initial set of widely variable scenarios through an iterative process, reaching an acceptable range. Choosing geostatistical realizations from previous iterations and using them as input in co-simulation, we can reproduce well-matched models Oliveira (2014).

Note that the image perturbation method we propose is different from the methodology used to modify other parameters. In this work, we only consider the spatial distribution of reservoir properties; we do not expect to achieve a perfect match, but to significantly improve the initial model's responses. For a complete history matching, it is essential to include all of the model's parameters and uncertainties.

2. Stochastic simulation methods

The first step in performing image perturbation is to select the geostatistical parameters to optimize and explore. Secondly, we choose a stochastic simulation method suitable for these parameters and the case. All parameters must be simulated with a continuous and conditional method, such as co-SGS or co-DSS or, for categorical variables, be dependent on a continuous variable. We used the Sequential Gaussian co-simulation to simulate continuous variables and the Truncated Gaussian Simulation for categorical variables that can be evaluated as a function of a continuous, pre-simulated variable.

The stochastic model reproduces the variability of the properties, namely the distribution function, which guarantees the frequency of the different classes of the histogram. A variogram reproduces spatial continuity of the studied variable. To use co-simulation, two more variables are necessary; a secondary image with the pattern that we want to honor in the following iteration and a correlation coefficient to gauge the strength of the pattern to be honored.

2.1. Sequential Gaussian co-simulation

The Sequential Gaussian co-Simulation (co-SGS) algorithm is based on the multiGaussian assumption of variable y(x). Hence, any local conditional expectation and conditional variance can be identified by simple kriging estimates. Any local Gaussian distribution is totally defined with the conditional mean and variance and the sequential simulation proceeds by generating a realization of local distributions according a random path (Goovaerts, 1997).

Equation (1) represents the simple kriging co-estimation,

$$Y^{*}(u) - m_y = \sum_{\alpha=1}^{n} \lambda_\alpha \left[Y(u_\alpha) - m_y \right] + \upsilon [B(u) - m_B] \tag{1}$$

where $Y^*(u)$ is parameter Y to be simulated in point u, m_y is the stationary mean of parameter Y, $Y(u_\alpha)$ is all the points simulated till that time, λ_α is the weight given to each point calculated by kriging estimation, $B(u)$ is the secondary variable in point u, m_B is the stationary mean of parameter B, and υ is the correlation coefficient between variable Y and B.

The correlation coefficient is an important parameter that measures how much the pattern should be honored in the next iteration. It can be between −1 and 1 and, for values near 1, the pattern is fully respected. As long as the value decreases, some flexibility is given for the following images, making it possible for the user to explore other similar options for the spatial distribution of that property.

2.2. Categorical variables - Truncated Gaussian simulation

The key idea of Truncated Gaussian Simulation is to choose a continuous property and set different classes inside the values of that property (Deutsch, 2002). For each class, a different value is set for the categorical attribute.

In traditional geostatistical modeling, porosity is simulated while

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