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A new framework for geostatistics-based history matching using genetic algorithm with adaptive bounds

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ABSTRACT

To maintain geological consistency, it is necessary to carry out the history matching process integrated to the geostatistical modeling. However, this integration leads to a complex optimization problem because the relationship between the input and output variables can be highly nonlinear. The purpose of this paper is to present a framework to integrate the history matching of production and seismic-derived dynamic data through a genetic algorithm with adaptive bounds. A new procedure is proposed to reduce the range of the parameters during the optimization process. The methodology was applied to a synthetic reservoir model with structural and petrophysical properties similar to a real reservoir and the results showed that it is possible to apply genetic algorithm in the integration of history matching and geostatistical modeling with feasible computational effort in terms of number of flow simulations.

1. Introduction

History matching is the incorporation of dynamic data, such as well pressure and production rates and 4D seismic-derived attributes, in the reservoir description process. It consists of changing the reservoir properties in a systematic manner with the objective of reducing the differences between the observed and simulated dynamic data. History matching can be carried out manually or assisted by computational tools. In assisted history matching, part of the process is driven by an optimization algorithm.

In conventional history matching procedures, petrophysical properties, such as porosity and permeability, are usually modified using multipliers. This procedure may generate models geologically inconsistent. This can be worse when changes are made regionally, because the modifications do not respect reservoir continuities. To maintain the geological consistency, respecting the spatial correlation (variogram) of petrophysical properties, the recommended procedure is to carry out the history matching integrated to the geostatistical modeling.

1.1. Integration of history and geostatistical modeling

In the last years, the number of works treating the history matching process integrated to the geostatistical modeling has been growing, showing the great efforts that have been made by many authors trying to improve this process. As a result of this effort, the gradual deformation is a relatively well-established method for geostatistical history matching, preserving geological structure during the history-matching process. Several authors have presented history matching procedures based on this technique. Caers (2003) proposed an algorithm combining gradual deformation, multiple-point geostatistics and a fast streamline-based history matching method.

Hoffman and Caers (2007) proposed a probability perturbation method to determine location and proportion of geologic bodies. The authors used a 1D optimizer to find the optimum geostatistical realization based on a parameter that controls how much the model changes in the iterative process. They firstly demonstrated the method on a synthetic example, where facies locations and proportions were simultaneously perturbed, and further, they also applied this method on a North Sea hydrocarbon reservoir. A stochastic search method (Neighborhood Algorithm) was applied by Suzuki and Caers (2006) to explore the search space for all geologically plausible model realizations, considering a similarity measure (among the best-matched realizations) for tuning the solutions.

Pilot points is another technique frequently applied in the geostatistical history matching. Recently, Da Veiga and Gervais (2012) used impedance residual map to automate the generation process of pilot points positions.

From the optimization point of view, the integration of history matching with geostatistical modeling is very complex because the relationship between the input parameters and the simulation output can be highly nonlinear. For example, in a reservoir with producers and water injection wells, one can guess that by increasing the permeability in a producer well region, the water rate in that pro-

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ducer tends to increase. On the other hand, changing a given geostatistical parameter that controls facies distribution (e.g., maximum correlation length and/or facies proportion), the effect of this change in water production can vary in an arbitrary way because there is no direct correlation between the two variables (facies distribution and water rate). Therefore, the study of optimization methods applied to the integration of history matching and geostatistical modeling requires more research effort.

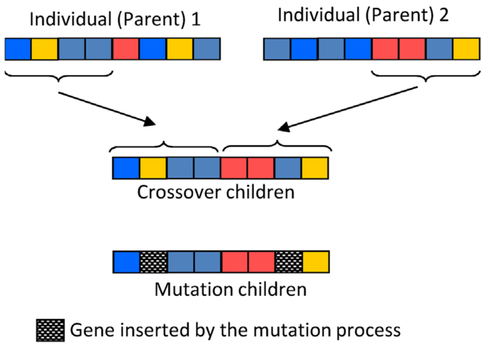

Fig. 1. Schematic representation of mutation and crossover operators.

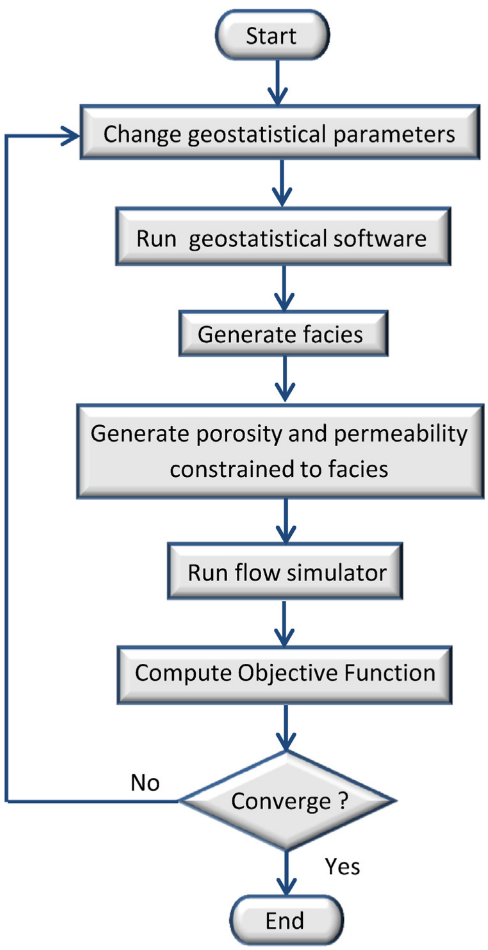

Fig. 2. General methodology flowchart.

Most of the optimization methods proposed to integrate geostatistical modeling and history matching are applied to simple cases. Although much effort has been dedicated to this theme, there are many challenges to overcome regarding the search for more efficient methods and the application of such methods in more complex cases.

1.2. Genetic algorithm

There are two main classes of optimization algorithms. The first is related to the gradient-based methods, which depend somehow on a descent direction in the search space. This kind of method (usually called the local method) normally has good efficiency (in terms of convergence). However, it is easily trapped in local minima. The second is known as global methods and does not depend on gradients. In general, they combine diversification and intensification strategies to better explore the search space and to increase the chance of finding global minimum.

Genetic algorithm (GA), which belongs to the second class, is a robust optimization method inspired by evolution theory. GA is a very flexible method, capable of solving a wide variety of optimization problems. The main driving processes of a genetic algorithm are selection, mutation and crossover. Crossover is the operation of redistributing genetic characteristics between two (parents) individuals of a population. The goal of the crossover operator is to retain good features from the previous generation. It enables the algorithm to extract the best genes from different individuals and recombine them into potentially superior children. Mutation is the mechanism by which a new individual is created by the introduction of a gene structure that is different when compared to other individuals in the population. The mutation mechanism creates a new offspring from one individual by changing one or more of its genes (Fig. 1).

The mutation rate (mr) controls the number of individuals generated by the mutation process and the crossover fraction (cf) controls the number of individuals generated by the crossover process. Supposing a population with 50 individuals and considering that 5 individuals are selected for the next generation by the selection operator, for cr = 0.6, 27 individuals of the next generation will be crossover children and 18 will be mutation children, representing mr = 0.4.

Considering the application of genetic algorithm in history matching, one of the great advantages is parallelism. Since the individuals of a given generation are independent, the flow simulation corresponding to these individuals can be distributed in a computer cluster; the higher the number of machines, the higher the speedup. This is an interesting advantage when compared to other methods that perform the objective function evaluation sequentially, which do not take advantage of this distributed environment.

Maschio et al. (2008) compared a direct search method and genetic algorithms in a history matching procedure. They used a sequence of images as one of the history matching parameters.

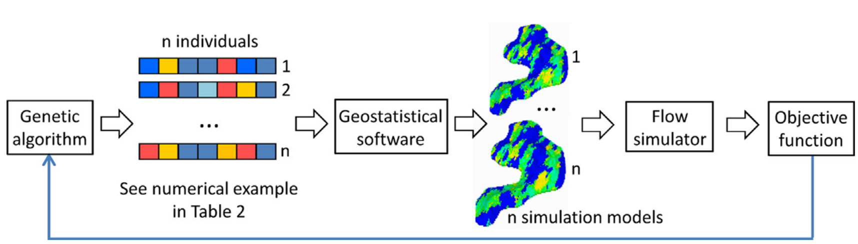

Fig. 3. Link between GA and geostatistics-based history matching.