Year 10, Number 6
93rd edition
May, 2015

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## Geostatistics-Based History Matching Using Genetic Algorithm with Adaptive Bounds

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*"The integration of history matching and geostatistical modeling leads to a complex optimization problem."*

### Introduction

To maintain geological consistency, respecting the spatial correlation (variogram) of petrophysical properties such as porosity and permeability, for example, the recommended procedure for history matching is to carry out the 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 work 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.

### Proposed methodology

The proposed methodology is composed of two main parts. The first part consists of a control module implemented in the MatLab platform. It is responsible for linking all components of the integrated process, such as the optimization algorithm, the geostatistical modeling software, the flow simulator and other routines for pre and post processing (e.g. generation of input files, reading of output simulator, objective function computation, etc.). The great advantage of developing an integrated methodology (such as that shown in the presented work), instead of using a commercial one, is the flexibility. Although in this paper the genetic algorithm is used in the optimization process, any other method can be used in the proposed framework. Other aspects, such as the way of composing the objective function, the link to any other geostatistical and flow simulators, are examples of flexibility that the proposed framework allows.

A control loop was built in the geostatistical software to input the matrix that composes a given generation (columns are the parameters used as input in the geostatistical modeling and rows are the individuals generated by the genetic algorithm – see example in Section 3). In this way, the number of geostatistical realizations, equivalent to the number of individuals per generation, is run in a unique call (via command line) of the software, which permits the speeding up of the process (Maschio, 2014). A schematic representation of the link between GA and geostatistics-based history matching can be found in Maschio *et al.* (2015).

The second part of the methodology corresponds to the new proposed procedure, incorporated to a genetic algorithm, whose main steps are described below:

1) Start the optimization process and perform $N_1$ generations;

2) Rank the individuals of the $N_1$ generations from the smallest to the largest values of the objective function;

3) Select a fraction of the best individuals and find the minimum and maximum values of each variable in the selected fraction (see a schematic example in Fig. 5 in which the individuals are ranked according to the Step 2) and assign the minimum value to the new lower bound and the maximum value to the new upper bound;

4) Continue the optimization process with $N_2$ generations with the new lower and upper bounds defined in Step 3;

5) Repeat Steps 3 and 4 until the defined stopping criterion is reached.

At the end of each block of generation, the best individuals are inserted into the first generation of the next block of generation, as can be seen in Fig. 1.

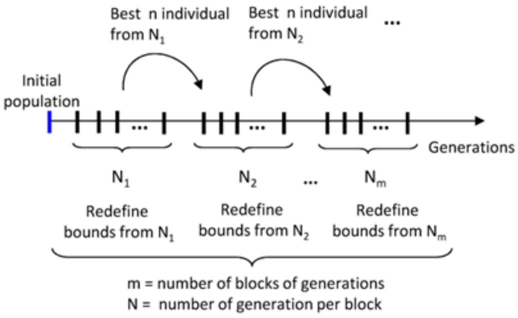


*Figure 1: Evaluation of N blocks of generations*

### Application

The proposed methodology was applied in a synthetic reservoir model (Fig. 2) with structural and petrophysical properties similar to a real reservoir. The reservoir is composed of sand bodies with interbedded shale. Synthetic logs of facies, porosity and permeability of 15 wells were considered as hard data to build the model. Porosity and permeability modeling is constrained to the facies distribution.

The reservoir model was discretized in a corner-point grid with 90×110×5 blocks (from which 22825 are active blocks), 60 m in size in the x and y directions (5400 x 6600 $m^2$) and 15 m (on the average) in the z direction and has 123 x $10^6$ $m^3$ of oil in place. The porosity and permeability in the shale were assumed to be constant and equal to 3% and 1 mD, respectively. The porosity varies between 15% and 26% and the permeability varies between 900 and 4180 md in the sand bodies. The objective function used in this work incorporates well (production and pressure) and 4D seismic-derived data (water saturation). Eight geostatistical parameters related to facies, porosity and permeability modelling (see Maschio *et al.*, 2015) were defined as uncertain.

The optimization processes, summarized in Table 1, were set to compare different mutation rates (mr) and crossover fractions (cf) and the percentage of best individuals (PI) - except for GA1 and GA2 that were run without this parameter - used to redefine the bounds, as proposed in this work. The stopping criterion defined is the maximum number of generations (15). Three

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blocks of generations with five generations per block were used, yielding 800 individuals (15 generations + initial population). The process GA3 was also run with different initial populations to demonstrate that the proposed method is not biased by a specific set of individuals.

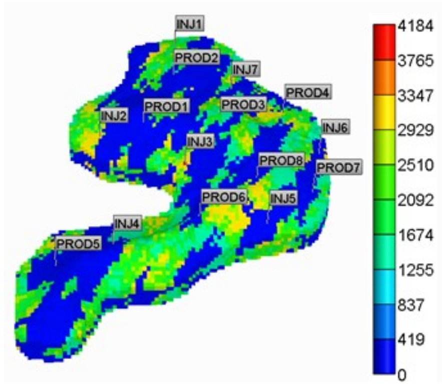


*Figure 2: Permeability (mD) of the reservoir showing sand bodies interbedded with shale*

*Table 1: Description of the optimization processes*

| Process | Nger | Nind | (mr) | (cf) | (PI) | (IP) |
|---|---|---|---|---|---|---|
| GA1 | 15 | 50 | 0.7 | 0.3 | - | IP1 |
| GA2 | 15 | 50 | 0.4 | 0.6 | - | IP1 |
| GA3 | 15 | 50 | 0.7 | 0.3 | 5 | IP1 |
| GA4 | 15 | 50 | 0.7 | 0.3 | 10 | IP1 |
| GA5 | 15 | 50 | 0.7 | 0.3 | 20 | IP1 |
| GA6 | 15 | 50 | 0.4 | 0.6 | 5 | IP1 |
| GA7 | 15 | 50 | 0.4 | 0.6 | 10 | IP1 |
| GA8 | 15 | 50 | 0.4 | 0.6 | 20 | IP1 |
| GA3a | 15 | 50 | 0.7 | 0.3 | 5 | IP2 |
| GA3b | 15 | 50 | 0.7 | 0.3 | 5 | IP3 |
| GA3c | 15 | 50 | 0.7 | 0.3 | 5 | IP4 |
| GA3d | 15 | 50 | 0.7 | 0.3 | 5 | IP5 |

## Results

The convergence of the optimization processes GA1, GA3, GA4 and GA5 are shown in Fig. 3. Overall, there is an improvement in the convergence using the proposed method. However, the best improvement in the convergence is observed for the processes GA3 and GA4 which combine higher population diversity with smaller percentage of individuals selected. Values of the objective function lower than 10, which is the case of GA3 (OF = 6.10), for example, represent an excellent match, for both seismic and well data.

GA3 process with different initial populations (GA3a, GA3b, GA3c and GA3d) also provided good convergence (similar to GA3). These results and other details are published in Maschio *et al.* (2015).

## Final remarks

1) A genetic algorithm is a suitable optimization method for the problem of history matching treated in this work. Good results were obtained with a suitable number of flow simulations. The use of the method in conjunction with a distributed simulation environment makes it a good candidate for real and more complex applications;

2) The proposed procedure to redefine the bounds parameters was successfully applied to the case studied and provided a significant improvement in the performance of the optimization process;

3) Better results were obtained with a higher diversification rate and a lower percentage of individuals selected to redefine the bounds.

4) The framework proposed in this paper can, in principle, be applied to any reservoir study, including real reservoir cases. Complex real cases may require high computational effort in terms of reservoir simulation and high time consuming can be a drawback for this methodology. However, increase in computational capacity nowadays makes possible its application in such cases. Besides, this framework has the advantage of exploring the distributing computing capabilities taking in consideration the parallel nature of genetic algorithm. For future works, it is recommended the study of local geostatistics techniques to improve the history matching parameterization.

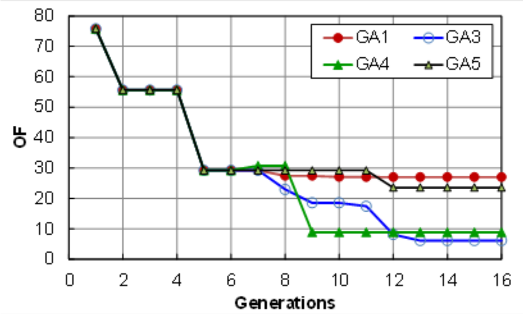


*Figure 3: Evolution of the objective function (PI=5%) for the best individual of each generation (see the definition of OF in Maschio et al. 2005)*

## References

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## About author:

Célio Maschio graduated in mechanical engineering from Unesp, obtained a MSc and a DSc degree in mechanical engineering from Unicamp and is a researcher at UNISIM.

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