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Probabilistic History Matching Using Discrete Latin Hypercube Sampling and Nonparametric Density Estimation

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"A correlation matrix to capture the influence of each attribute on the reservoir outputs is proposed."

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Introduction

This text is a compilation of a paper published in *Journal of Petroleum Science and Engineering* (Maschio and Schiozer, 2016), which proposes a new iterative procedure for probabilistic history matching using a discrete Latin Hypercube (DLHC) sampling method and nonparametric density estimation.

The iterative procedure consists of selecting a set of models based on the history matching quality (normalized misfit) to generate histograms. The histograms are smoothed and used to estimate marginal probability densities of reservoir attributes. Three selection methods are evaluated. One of them is based on a global objective function (GOF) and the others are based on a local objective function (LOF), which is composed of influenced reservoir responses identified with the aim of a correlation matrix.

Robustness, efficiency and facility of implementation are the key features of the proposed methodology.

Proposed Methodology

The general steps of the proposed methodology are listed below:

1. Parameterization: in this work, each attribute is discretized on a given number of levels. The advantage is that, working in a discrete domain, it is possible to deal with categorical uncertainties, such as reservoir attributes represented by tables (PVT and relative permeability, for example), making the methodology very flexible.
2. Generation of samples using the DLHC method. The initial models (in the first iteration) are sampled from the prior distribution.
3. Run flow simulations.
4. Computation of the normalized misfit.
5. Selection of models based on match quality measured by the normalized misfit. The output of this step, in the form of histograms, is the input for the next step.
6. Estimation of non-parametric marginal probability distribution for each attribute.
7. Return to Step 2 if the defined number of iterations is not reached.

Model Selection Methods

Three methods of selecting models were proposed in this work. The first is a simple method based on a global function (considering all reservoir responses to be matched) and the others (Methods 2 and 3) are based on a local objective function computed according to the correlation matrix. In Method 2, for each model, a local objective function is computed based on the values of NQD (Normalized Quadratic Deviation) of the influenced functions. The models are then sorted based on LOF and a percentage is selected. In Method 3, instead of selecting the models based on a fixed percentage, a cutoff value of NQD is used.

Correlation Matrix

A correlation matrix to capture the influence of each attribute on the reservoir outputs is proposed. This matrix is composed of m columns and n rows, m being the number of functions and n the number of attributes. Each element of this matrix is the correlation coefficient between each attribute with respect to each reservoir's responses (local OF). A cut-off value (Rc) is used to select the influenced responses based on the correlation coefficient. The models are thus selected based on the influenced functions.

Tests performed by Maschio and Schiozer (2016) suggest that moderated correlation (around 0.3) is adequate. This can be explained by the fact that, usually, very few reservoir responses are affected by a very strong correlation. According to the proposed criterion, if a given attribute does not influence any local OF based on the value of Rc, its probability distribution is not changed in the current iteration. Thus, most attributes keep their prior distribution for many iterations, maintaining the high variability of the solutions. On the other hand, if a very weak correlation is chosen, the tendency is that all functions are considered.

Nonparametric Density Estimation

Once the models are selected using one of the methods mentioned in the previous section, the next step of the methodology consists of estimating a nonparametric marginal density for each attribute based on a kernel estimation method. This procedure generates a smooth nonparametric estimate based on the histogram (Fig. 1a) that resulted from the model selection.

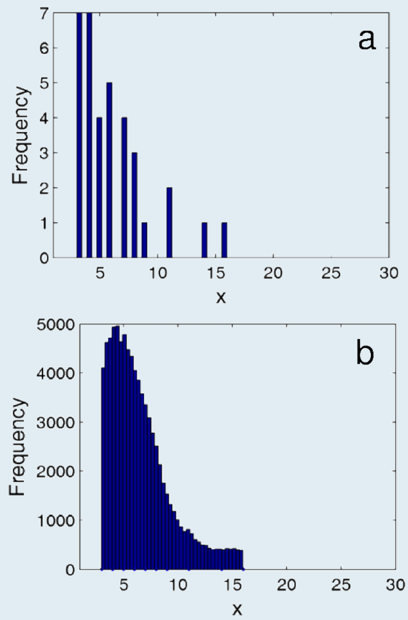

Figure 1: *Nonparametric density estimation.*

The procedure is composed of the following steps:

a) Using a kernel-density estimation technique, generate an empirical cumulative distribution. The level of smoothing in the estimates is controlled by the bandwidth parameter set in the kernel estimator.
b) Generate a large random vector from a uniform distribution U(0,1).
c) Transform uniform random values back to the scale of the original data using a linear interpolation over the grid of CDF estimates. This procedure generates a smoothed histogram (Fig. 1b), which is transformed into a discrete PDF according to the number of intervals. This new PDF is then used to generate new samples in the next iteration. This smoothing is necessary because the histogram generated from the filtering may present discontinuities, as shown in Fig. 1a. This process restores the continuity and allows new samples to be generated in the next iterations in those discontinuous intervals. In other words, this procedure prevents premature level elimination.

The marginal densities obtained in this step are used as input for the sampling in the next iteration.

Application

The methodology was applied in the UNISIM-I-H benchmark case, which is a model based on Namorado field, Campos Basin, in Brazil (http://www.unisim.cepetro.unicamp.br/benchmarks/br/unisim-i/unisim-i-h). Eight iterations with 450 samples per iteration were run.

"The smoothing procedure incorporated in the proposed probability estimation avoids premature level elimination."

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Results

Figure 2 shows a comparison of Methods 1, 2 and 3 in terms of NQD along the iterations. For each iteration, there are 450 points (450 models per iteration) representing the average NQD of the 64 OF included in the study. The solid lines represent the global mean of NQD over all models corresponding to each of the iterations. This plot shows a better convergence rate related to Methods 2 and 3 when compared with Method 1, which shows the benefits of using the correlation matrix (Methods 2 and 3).

The robustness of the proposed method was tested repeating it 10 runs with the same configurations. The results of the 10 runs, in terms of NQD vs. iteration, were very similar and exhibited the same behavior in terms of variability along the iterations, showing the stability of the method through the consistency of the results, which are shown in Maschio and Schiozer (2016).

Figure 3 shows a comparison between the PDF at the end of the first and the eighth iterations and Figure 4 shows the improvement in quality matching, in terms of NQDS, comparing Iterations 1 and 8. More details can be found in the full version of the paper.

Besides the application in history matching presented in this text, another successful application of the proposed method in the area of production strategy optimization can be found in Hohendorff Filho *et al.* (2016).

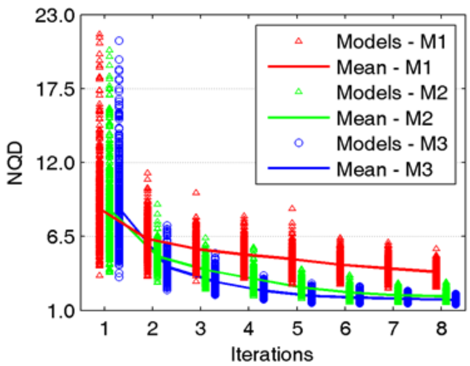

Figure 2: *Evolution of NQD along the iterations for Methods 1, 2 and 3.*

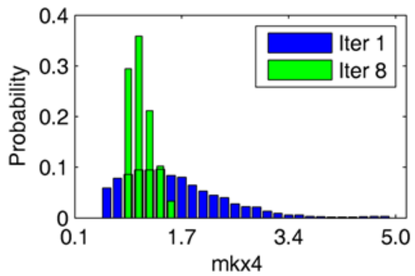

Figure 3: *Comparison of PDF after Iterations 1 and 8 (Method 3).*

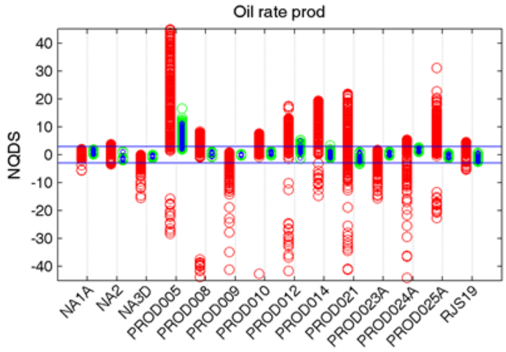

Figure 4: *NQDS for oil rate after Iterations 1 and 8.*

Final Remarks

A new iterative procedure for probabilistic history matching was proposed in this work. The application of DLHC in the iterative process is an interesting approach because, along the iterations, the selection of the best models allows for the improvement of the probability redistribution, tunneling the search space as the sampling process is gradually intensified in the regions of high probability. The smoothing procedure incorporated in the proposed probability estimation avoids premature level elimination at the beginning of the process.

Efficient selection methods were proposed in order to avoid the collapse of the samples. The Methods 2 and 3 (selection of models based on the correlation matrix) yielded better results when compared to Method 1, which uses a global objective function.

Finally, the main contribution of this work is a robust workflow for probabilistic history matching, suitable for application in practical and complex cases.

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References

Maschio, C.; Schiozer, D. J. "Probabilistic history matching using discrete Latin Hypercube sampling and nonparametric density estimation", Journal of Petroleum Science and Engineering, v. 147, pp. 98-115, 2016. http://dx.doi.org/10.1016/j.petrol.2016.05.011

Hohendorff Filho, J. C. V.; Maschio, C.; Schiozer, D. J.; "Production Strategy Optimization Based on Iterative Discrete Latin Hypercube", Journal of the Brazilian Society of Mechanical Sciences and Engineering. Published online: March 2016. http://dx.doi.org/10.1007/s40430-016-0511-0

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