History matching under uncertain geological scenario

Hyucksoo Park[1] and Jef Caers[2]

Abstract The main interest lies in obtaining multiple history matched models under uncertain geological scenario. Within a Bayesian framework, the only exact sampling technique for obtaining multiple such Earth models is the rejection sampler, however, it is extremely inefficient for most practical applications. To handle this problem, we propose to split the problem in two parts: the first part is the traditional question of history matching for a given geological scenario, the second part is to determine the probability of that scenario given the production data. Comparison with the rejection sampler shows that our technique is accurate at a fraction of the cost of rejection sampling.

Methodology

To handle uncertain geological scenarios in a consistent and repeatable mathematical framework, the Bayesian approach is applied.

$$\mathrm{P}(\mathbf{M}|\mathbf{D}) = \frac{\mathrm{P}(\mathbf{D}|\mathbf{M})\mathrm{P}(\mathbf{M})}{\mathrm{P}(\mathbf{D})} \cong \mathrm{P}(\mathbf{D}|\mathbf{M})\mathrm{P}(\mathbf{M}) \quad (1)$$

where, $\mathbf{M}$ is a random vector representing the Earth model (which we will assume has discrete random variables) and $\mathbf{D}$ is a random vector representing data.

In addition to the gridded model $\mathbf{M}$, some parameters related to the construction of this gridded model, such as a geological scenario (which variogram, training image, Boolean model type and etc.), is uncertain. To explicitly account for this uncertainty, equation (1) is rewritten as,

$$\mathrm{P}(\mathbf{M},\boldsymbol{\Theta}|\mathbf{D}) = \sum_{\boldsymbol{\theta}} \mathrm{P}(\mathbf{M}|\,\boldsymbol{\Theta},\mathbf{D})\mathrm{P}(\boldsymbol{\Theta}|\mathbf{D})$$

where, $\boldsymbol{\Theta}$ is a discrete random variable representing geological scenario uncertainty. One can assume the possible number of scenarios to be limited.

The above equation now divides the history matching problem into two following parts.

[1]Stanford University, Energy Resources Engineering, 367 Panama St, Stanford, CA 94110, USA hyuckso0@stanford.edu

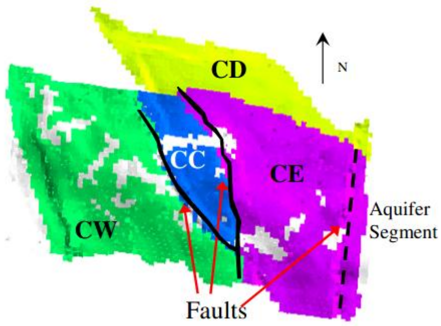
[2]Stanford University, Energy Resources Engineering, 367 Panama St, Stanford, CA 94110, USA jcaers@stanford.edu

Part 1, $\mathrm{P}(\mathbf{M}|\mathbf{\Theta},\mathbf{D})$ describes a posterior probability of a model $\mathbf{M}$ given $\mathbf{\Theta}$ and $\mathbf{D}$. Since $\mathbf{\Theta}$ can be a variogram or a training image and it is fixed as one of the discrete outcomes, this problem can be solved by a regional PPM (Caers, J., Hoffman, T., 2006) with a fixed variogram or training image.

Part 2, $\mathrm{P}(\mathbf{\Theta}|\mathbf{D})$ is the pre-posterior of the scenario $\mathbf{\Theta}$ with given the data $\mathbf{D}$, in other words it models the updated uncertainty on the prior geological scenario $\mathbf{\Theta}$ now given the data $\mathbf{D}$. We propose a distance-based approximation method for estimating this probability directly.

Example

Here a western African reservoir case (figure 1) with three different training images is used for its uncertain geological scenario. Initially 4 production wells / 4 injectors are producing / injecting from 0 to 2000 days (figure 2). 30 history matched models will be obtained based on the production data. The new well will be placed at 2000 day and be used for the validation of prediction power of proposed methodology with rejection sampler.



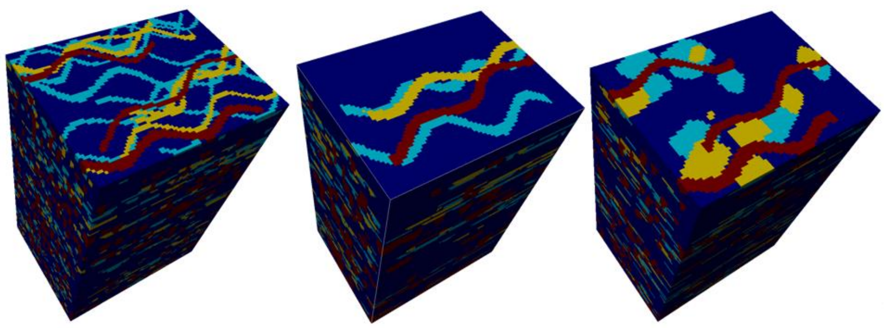


Figure 1: Reservoir description (CW, CC, CE have communication but CD has no communication) (above) and 3 Training Images which represent the uncertain geological scenario (bottom).

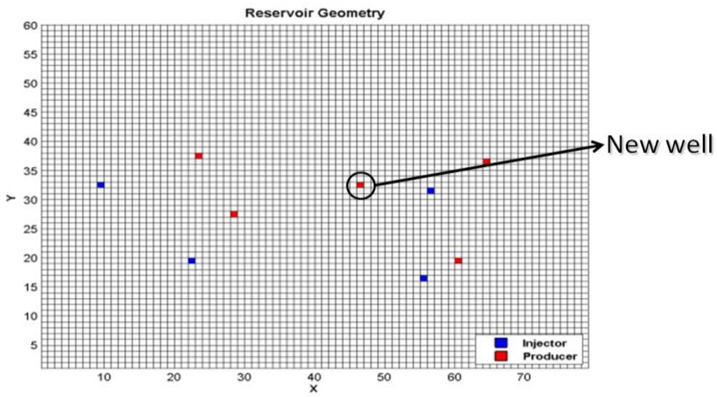


Figure 2: Reservoir geometry

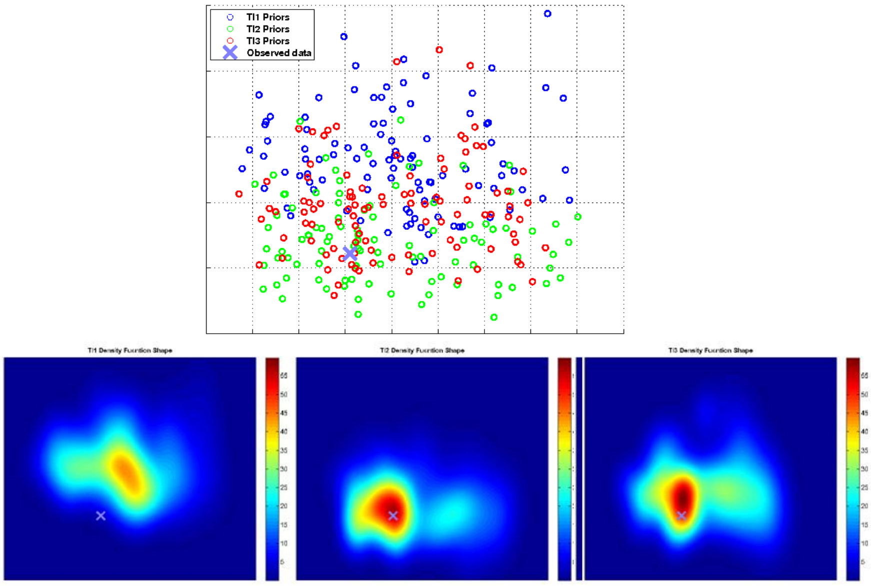
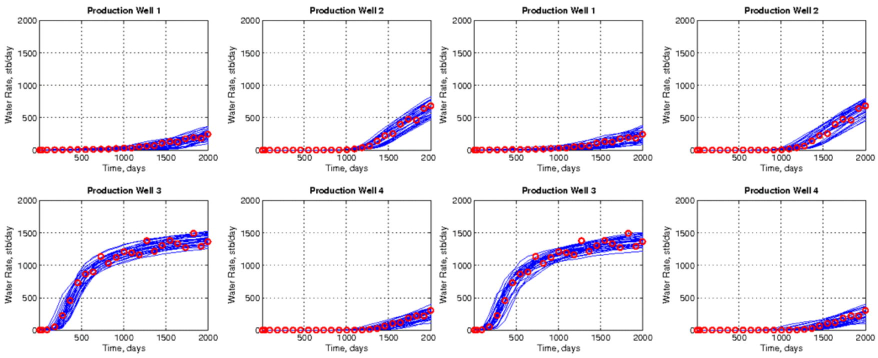


Figure 3: Scoping runs for 3 TIs (above), Adaptive kernel smoothing results for each TI (bottom from left to right TI1, TI2, and TI3).

In order to estimate the probabilities of each TI with given data, we perform a number of scoping runs and calculate their mutual distance in terms of forward model responses. Figure 3 Shows the MDS plot. A simple kernel smoothing allows then estimating likelihood at all locations in the MDS plot, including the production data location. Simple application of Bayes' rule then models the pre-posterior probabilities of each TI given the data. Regional PPM is then used to obtain history matched models from each TI (figure 4). We compared the 30 history matches obtained in this way with 30 history matches by rejections sampler as well performance prediction on a newly planned well. (figure 5). Such comparison is favorable at a fraction of the CPU cost of the rejection sampler.



Regional PPM

Rejection Sampler

Figure 4: 30 history matching results for 4 production wells by regional PPM (left), and rejection sampler (right).

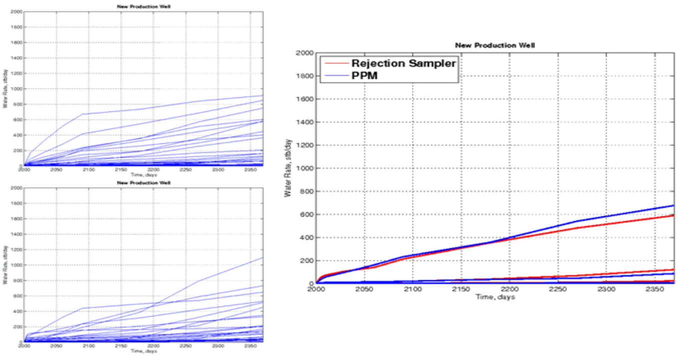


Figure 5: Prediction for 1 year of new well performance by regional PPM (left up), rejection sampler (left down) and P10 P50 P90 plot comparison.

Bibliography

[1] Caers, J., Hoffman, T., 2006. The probability perturbation method: a new look at Bayesian inverse modeling. Mathematical Geology

[2] Borg, I., Groenen, P., 2005. Modern multidimensional scaling: theory and applications. Springer series in statistics. Springer.

[3] Honarkhah, M., and Caers, J. "Stochastic Simulation of Patterns Using Distance-Based Pattern Modeling", 2009

[4] Scholkopf, B., Smola, A., 2002. Learning with kernels: support vector machines, regularization, optimization, and beyond.