A neighborhood algorithm (NA) for modeling dual-medium scenario uncertainty from production data

Sarah Alsaif and Jef Caers
Energy Resources Engineering Department
Stanford University, USA

Abstract

Uncertainty quantification and history matching have been a challenge in reservoir forecasting, especially in naturally fractured reservoirs (NFRs) where the nature of the fractures is unknown resulting in large prior uncertainty. Multiple geological scenarios are generated for NFRs and a single best fit model is not sufficient for decision-making under large uncertainty. In this report, we propose a Neighborhood algorithm (NA) stochastic search method to search for multiple models that match the historical production data rather than producing one single best fit model. Uncertainty is then quantified by calculating posterior probabilities using the data generated from NA. The method is illustrated with an application to a synthetic reservoir model analogous to fractured reservoirs in the Middle East. NA is proved to be an efficient and a fast way to calculate the posterior probabilities and quantify uncertainty.

Introduction

Uncertainty quantification in naturally fractured reservoirs (NFR) is a challenging task. Proper modeling of NFRs is critical in forecasting their behavior. Early water breakthrough and poor oil production are common risks in dealing with NFRs. High uncertainty in natural fractures and their properties leads to multiple numbers of possible geological scenarios and hence a large prior uncertainty.

The synthetic fractured reservoir used in this case is obtained from a work done by Andre Jung (Jung et al., 2013). In their work, Jung et al. generated discrete fracture network (DFN) models of all potential geological scenarios. A total of 156 DFN scenarios were generated utilizing all available sources of data about the nature of fractures in the reservoir. Based on the fracture connections in each grid cell, DFN models were translated into dual-medium binary training images. Only cells with connected fractures were considered as dual-medium cells while the rest are considered single-medium cells. In this work, we will continue on the work of Jung and define a static similarity distance between all the realizations. Then we will apply NA to explore that metric space for multiple models that match the data. From these models we will then calculate posterior probabilities of geological scenarios which can be used in further history matching or uncertainty quantification studies.

We will first re-introduce the case study, the prior space of dual medium models constructed by Jung et al. Then we will develop the proposed NA method.

Case study description

A synthetic reservoir model was constructed in analogy to fractured reservoirs in the Middle East. The main structure is a North-South anticline with buckle folds on both sides. It extends 18.6 km in X (East-West) and 15.7 km in Y (North-South). It is represented by 102x86 grid cells with 600x600 ft horizontal dimensions. The model consists of one layer with 25 ft thickness. Initial oil-water contact is at 6100 ft and there is also pressure support from the underlying water aquifer. The reservoir is produced with 27 producers and 18 injectors (peripheral waterflooding) as shown in Figure1. Water injection is performed under a constant bottom hole pressure of 4000 psi and maximum allowable rate of 5000 stb/day. The total fluid production at each well is restricted to 2000 stb/day. Throughout the total production period, the reservoir pressure is always above the bubble point pressure and hence no free gas exists. Streamline simulator using the dual-porosity single-permeability model is used to calculate the flow responses. The porosity and permeability of the matrix are set constant at 10% and 200mD, respectively.

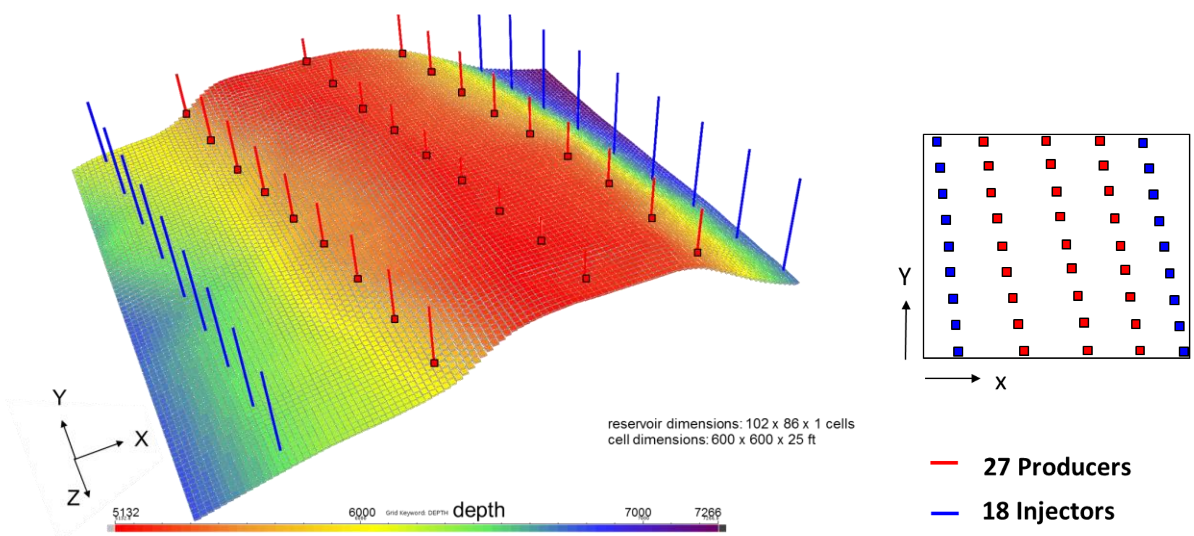

Figure 1 Reservoir model used in this study (left). Producers and injectors layout (right)

The reservoir is produced in three phases as shown in Figure 2. In this report, the forward simulation responses in the NA workflow are generated from phase 1 with 6 producers and 6 injectors.

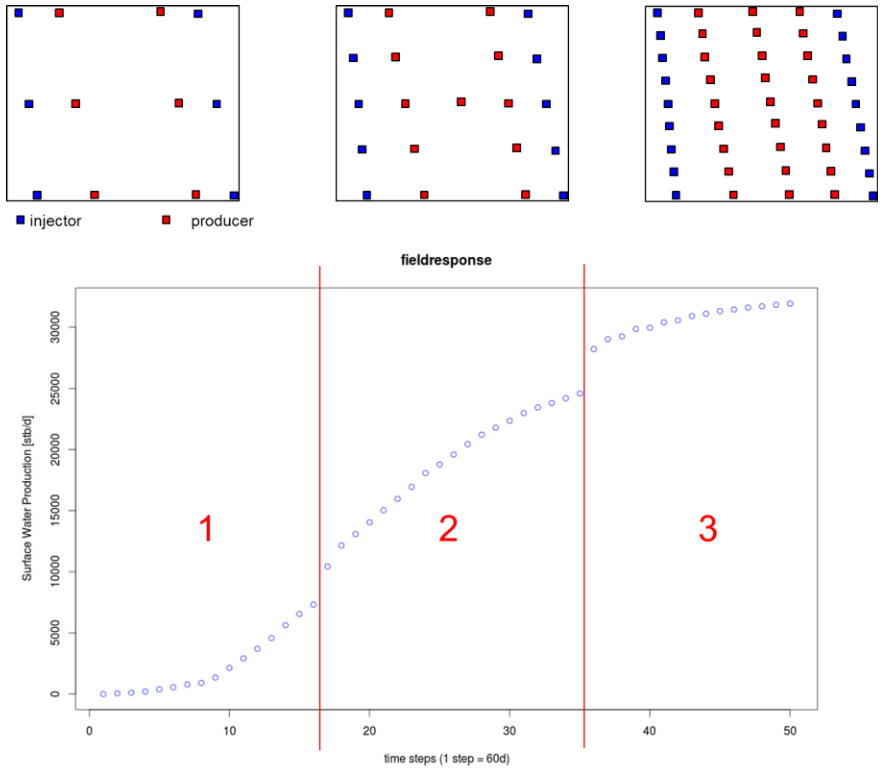

Figure 2 Three phases of the production plan showing the surface water production and the number of producers and injectors in each case

DFN generation and translation to dual-medium models

Multiple geological scenarios are usually associated with naturally fractured reservoirs when interpreting different sources of data such as borehole imaging, well logs, seismic and outcrop data. In a previous work done by Andre Jung, full factorial design experiment was performed taking into account both conceptual and parameter uncertainty leading to 156 possible DFN scenarios. Table 1 shows the parameter variations used in the experimental design process.

Table 1 Parameter variations used in experimental design resulting in 156 scenarios

Presence of second fracture set	Yes	No	
Fracture set 1: size (powerlaw distribution of equiv. radius with D = 2, trunc. at 3,000 ft, aspect ratio 2:1)	400 ft	600 ft	
Fracture set 2: size (powerlaw distribution of equiv. radius with D = 2, trunc. at 3,000 ft, aspect ratio 2:1)	200 ft	400 ft	
Fracture set 1: trend of pole vectors (orientation distribution: Fisher with dispersion = 8)	0◦	45◦	
Fracture set 2: trend of pole vectors (orientation distribution: Fisher with dispersion = 8)	30◦	60◦	
Fracture set 1: intensity correlated with folding (curvature)	No	Weak	Strong
Fracture set 2: intensity correlated with fracture corridor (seismic coherence)	No	Weak	Strong

DFN models are upscaled to effective properties and then translated into dual-medium reservoir models. Cells that do not have sufficient fracture connectivity are considered single-medium and the rest are dual-medium. Since porosity is highly correlated with fracture intensity, a porosity cutoff is used as means of deciding which cells are dual-medium and which are single-medium. Dual-medium cells are populated with effective properties of the fractured medium (fracture porosity phi, fracture permeabilities (kfx, kfy, kfz), and the shape factor sigma which describes the fracture/matrix exchange while single-medium cells are populated with only the matrix properties (Figure3). Four realizations were generated for each geological scenario leading to a total of 624 realizations.

a)

b)

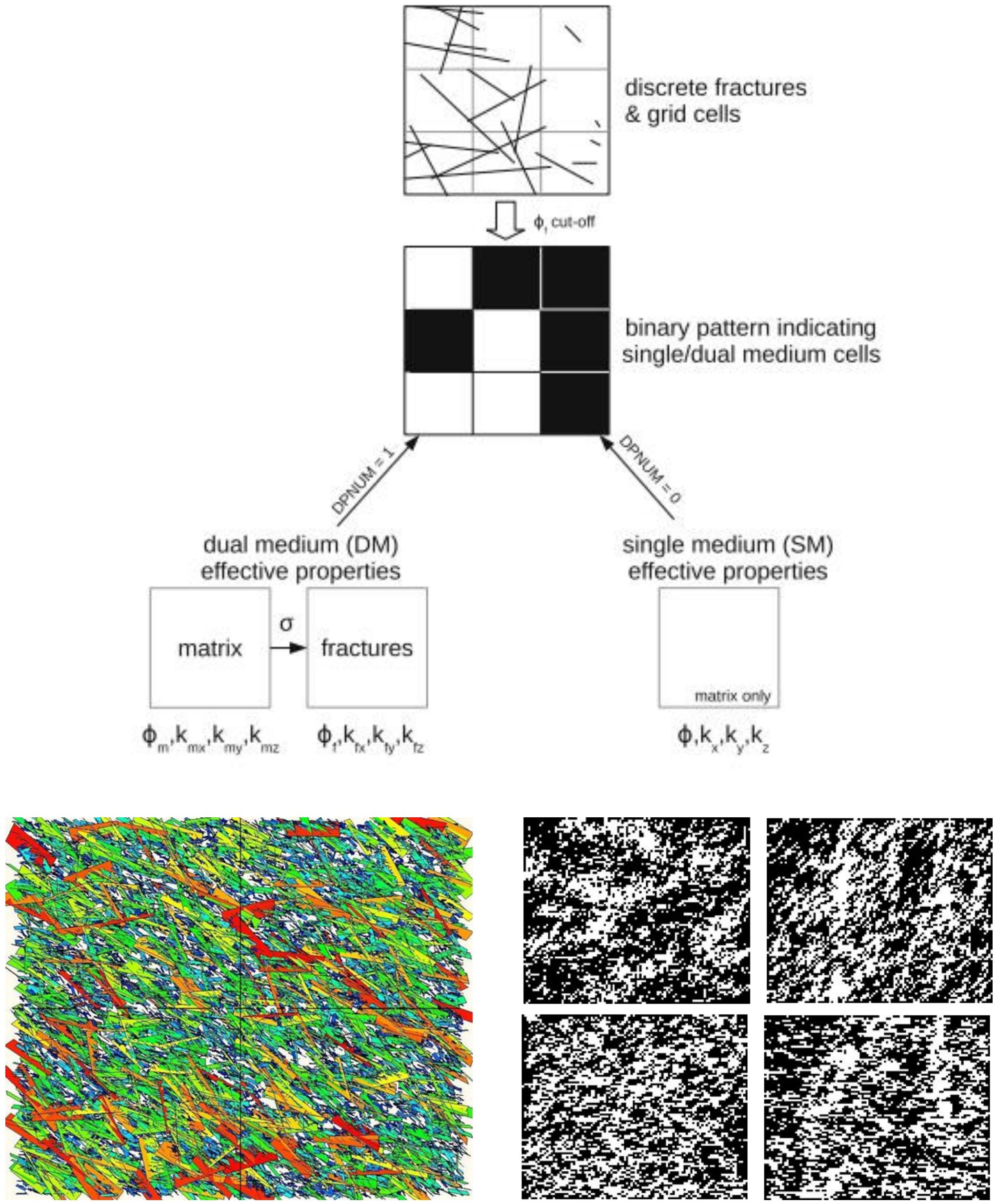

Figure 3 Translation of DFN to dual-medium models b) 4 possible DFNs (left) and 4 binary training images associated with them. (adapted from Jung et al., 2013)

Methodology

Defining the prior space

We define a prior uncertain space by a distance function. The modified Hausdroff distance (MHD) was used as a similarity measure since it is best for matching objects based on their edge points (Dubuisson and Jain, 1994). MHD was computed for all the 624 binary realizations. Multidimensional scaling (MDS) and K-medoid techniques (Maechler et al., 1994) were then applied in order to group the similar scenarios into clusters and select one representative scenario for each cluster (Figure4).

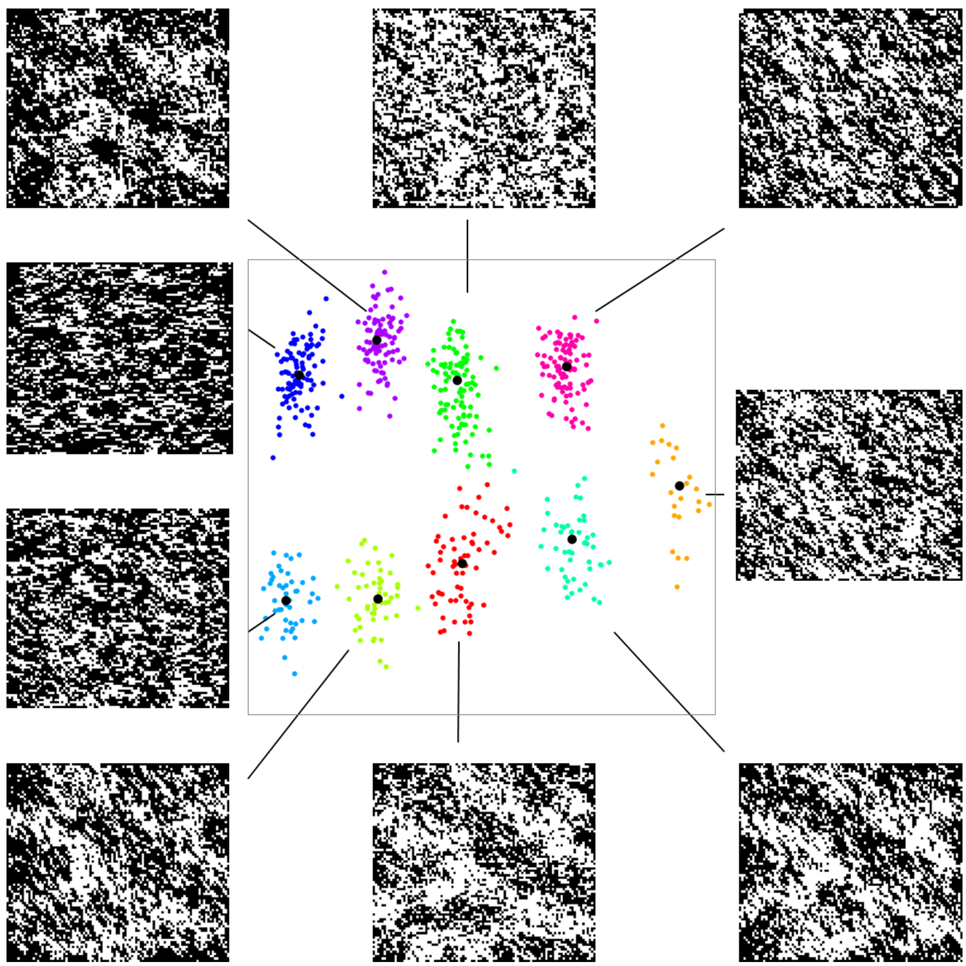

Figure 4 MHD is mapped into metric space and 9 representative training images were identified suing MDS and k-medoid clustering

As shown in the Figure 4 above, 9 scenarios were selected and they were confirmed to reasonably capture the uncertainty by Jung.

Neighborhood Algorithm

The neighborhood algorithm is a stochastic search method developed initially for seismic inverse problems (Sambridge 1999a) and then adapted for reservoir characterization and history matching (Demyanov and Subby, 2004). Although it is designed for multi-dimensional parameter space, it can be reformulated and applied to a metric space that is defined by a distance matrix (Suzuki, 2008). NA explores the prior space for multiple minimums and it partition the space into Voronoi cells as the evaluation proceeds (Suzuki, 2008).

The workflow involves two major phases:

1- Searching phase which explores the prior space for low misfit models.
2- Probability estimation phase where posterior probabilities of scenarios are calculated.

Phase 1: searching for low misfit models

NA follows these steps:

1. We start with a small number of models separated by large distances in the prior space. Flow simulation is then performed for these models and the mismatch with the field data is calculated using the following objective function $O(m_i)$

$$O(m_i) = \frac{1}{N_{time}} \sum_{k-1}^{N_{time}} \{g_k(m_i) - d_k\}^2$$

Where $g_k(m_i)$ is the simulation response for model m_i at time k and d_k is the field data at time k. Since we are matching water cut (WC) data, the objective function used consists of two parts; the first part is the objective function using breakthrough times and the second part is using WC data. The above equation was used for computing both parts of the objective function.

The parameter space is then partitioned into Voronoi cells by associating the prior models with the closest simulated model.

2. Selection probability is calculated for each cell using the following equation:

$$p(m_i) = exp\left\{-\frac{1}{T}\frac{O(m_i)}{M}\right\}$$

Where M is the number of prior models in the cell that are not simulated yet and T is determined such that the total probabilities over the entire Voronoi diagram equals 1 (Suzuki, 2008). One cell is randomly selected based on the calculated selection probability and the next model is chosen randomly from that cell.

3. Flow simulation is performed and objective function is evaluated for the new selected model and the selection probabilities are updated for the next trial.

Steps 2 and 3 are repeated until the number of required matched models is obtained. Figure5 (Suzuki, 2008) is a schematic illustrating the procedure:

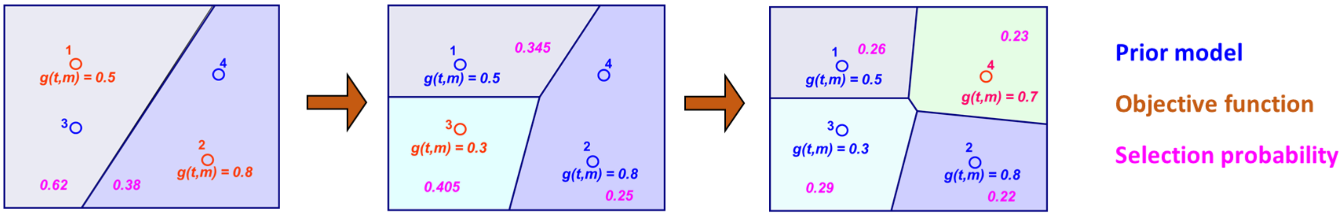

Figure 5 A schematic of the Neighborhood algorithm workflow (after Suzuki, 2008)

Phase 2: probability calculations

The output of NA are a set of models (search from the initial prior set) that are closely matching production data. However, NA also produces tessellations in metric space and with each model is associated an area in metric space. In this section we introduce a method for calculating the posterior probability of the nine scenarios using NA.

First, we associate with each model evaluated, a likelihood density function calculated from the objective function

$$f = \exp(-\frac{O(m_i)}{\alpha})$$

where α is a scaling parameter determined using the *T* value in the selection probability equation. This density is associated with a model within a pologyn, do to calculate probabilities from densities, we need to make sure that the densities integrate to one. The total integral is:

$$\sum_{i}^{M} f_i \times A_i = c$$

where M is the total number of simulated models, A_i is the surface area associated with each model. The probability for each model is calculated using the following equations:

$$P(model|data) = \frac{f_i}{c} \times A_i$$

Then, each models is traced back to the cluster that it belongs to and the probabilities of the 9 training images identified by MDS and K-medois clustering earlier are calculated based on the following equation:

$$P(scenario|data) = \sum_{i \in Sci} \frac{f_i}{c} \times A_i$$

Results and discussion

Applying NA to the fractured reservoir described in the case study earlier, the following Voronoi diagrams are obtained as the function evaluation proceeds. In Figure 6, low objective function regions are represented in red and high objective function regions are represented in blue.

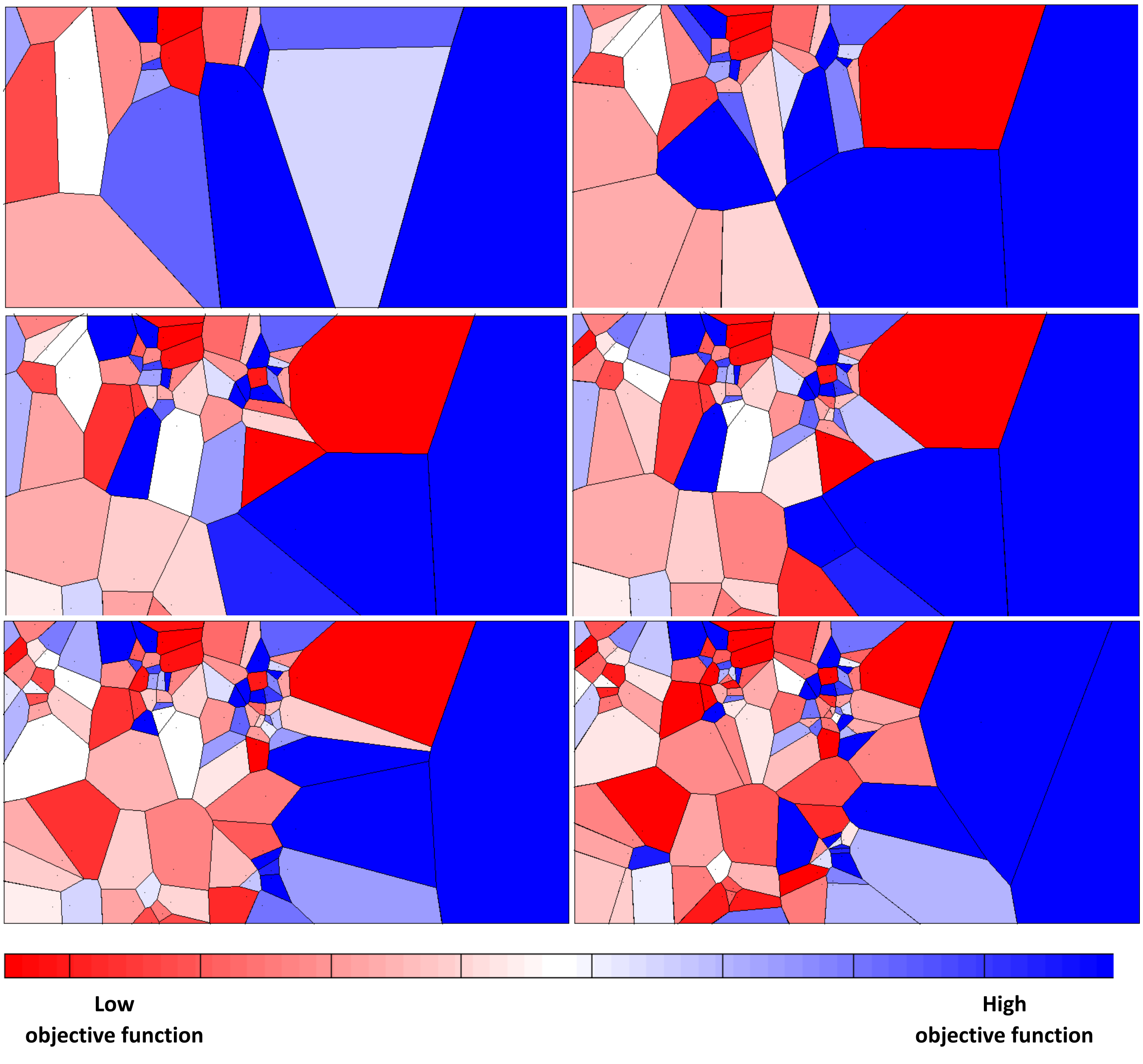

Figure 6 NA partitioning of the prior space into Voronoi cells as it proceeds. The red color indicates low objective function while the blue color indicates high objective function.

It can be seen from Figure 6 that NA visits (zooms into) the regions with low objective functions dividing them into finer cells. Comparing the Voronoi cells diagram at the end of NA with the one where all the models are simulated (Figure 7) shows that as NA proceeds, it converges to the 'right' solution and we can detect areas with low objective functions without simulating all the models.

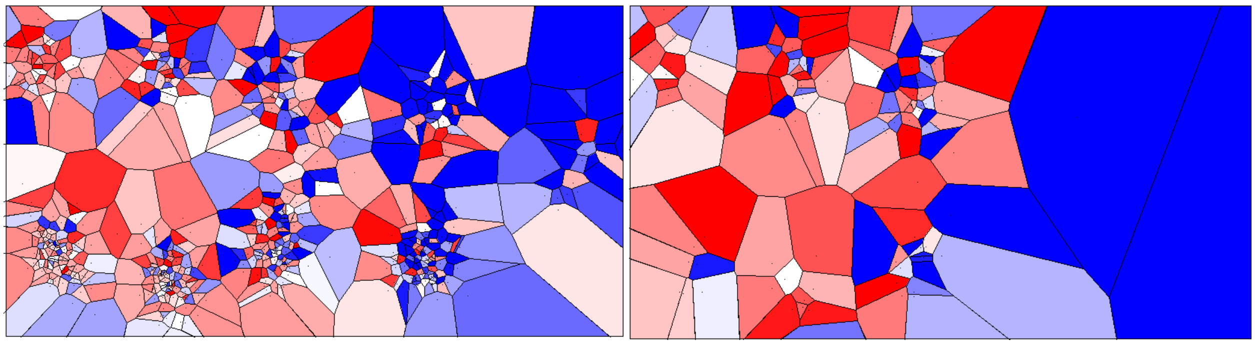

Figure 7 The Voronoi diagram when all the models are simulated (left) and the Voronoi diagram at the end of NA (right).

The figure below shows the matched models with 10% lowest objective functions at the end of NA. The black lines are the simulated responses, the red line is the field data and the purple lines are the simulated responses for the rest of the 624 models that were not selected during NA.

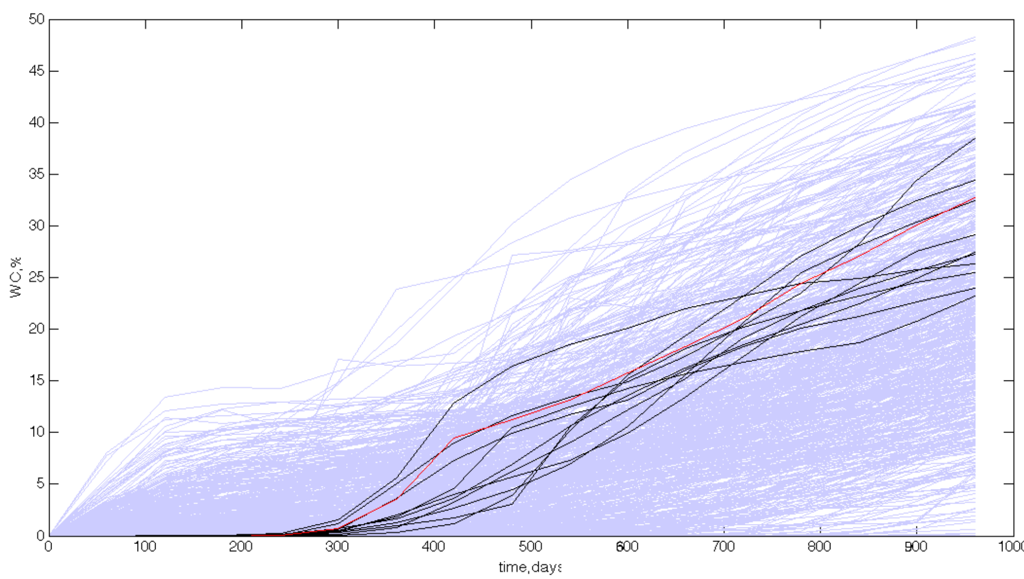

Figure 8 Best matches with the 10% lowest objective function models

Probability calculations results

Posterior probabilities for the 9 training images are shown in Table 2.

Table 2 Posterior probabilities of the 9 training images (TI)

TI	Probability, %
1	42.6
2	0
3	0
4	39.2
5	0
6	0
7	0
8	0
9	18.2

Conclusions

In this report, a Neighborhood algorithm method was introduced as a relatively fast and an efficient way of quantifying uncertainty in naturally fractured reservoirs (NFRs). The nature of fractures in NFRs is associated with large uncertainty. The stochastic search method was applied to a synthetic NFR model presented by Andre et al. in previous work. In their work, Andre et al. generated discrete fracture network (DFN) models and translated them into binary dual-medium models (training images). These training images were represented in the prior space by Hausdorff distance and NA was applied to search the space for matched models.

Taking into account all available data, NA efficiently searched the prior space for multiple models that honor the historical production data. However in this study we do not focus on history matching: using the information generated by NA, posterior probabilities were then calculated and fewer scenarios were selected and can be used for further history matching or uncertainty quantification studies.

References

Dubuisson, M.-P., & Jain, A. K. (1994). A modified Hausdorff distance for object matching. *Proceedings of the 12th IAPR International Conference on Pattern Recognition, 1994. Vol. 1 - Conference A: Computer Vision Image Processing* (Vol. 1, pp. 566 –568 vol.1). Presented at the, Proceedings of the 12th IAPR International Conference on Pattern Recognition, 1994. Vol. 1 - Conference A: Computer Vision Image Processing. doi:10.1109/ICPR.1994.576361

Jung, A., Fenwick, D. H., & Caers, J. (2013). Training image-based scenario modeling of fractured reservoirs for flow uncertainty quantification. Computational Geosciences, 17(6):1015-1031. DOI 10.1007/s10596-013-9372-0.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., & Hornik, K. (2011). Cluster Analysis Basics and Extensions. R package version 1.14.1.

Malcolm Sambridge, Geophysical inversion with a neighborhood algorithm - I: Searching a Parameter space, Goephys. J. Int., 1999.

Suzuki, S. & Caers, J. (2008). A distance-based prior model parameterization for constraining Solutions of spatial inverse problems. *Mathematical Geosciences*, 40(4):445-469. DOI 10.1007/s11004-008-9154-8.

Vasily Demyanov, Sam Subbey and Mike Christie, Uncertainty assessment in PUNQ-S3: Neighbourhood algorithm framework for geostatistical modeling, Proceedings of ECMOR IX, 2004