Geological Heterogeneity Within and Between Unstructured Grid Blocks

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Heterogeneity in a hydrocarbon reservoir generally refers to a nonuniform, non-linear spatial distribution of rock properties. Simulation of flow in three dimensional reservoirs involves complex geometry and geology; the use of unstructured grids permits adequate resolution of important features such as fault, channels and deviated wells. Within an unstructured grid we may have multiple facies and/or subsequences; this can introduce problems related to searching for relevant data in kriging and accounting for connectivity of facies within and between adjacent blocks. This note documents one approach to account for geological heterogeneity within and between unstructured grid blocks. Conventional indicator kriging and simulation methods are used to simulate connected blocks one at a time, with successively increased conditioning to previously simulated locations. Facies connectivity is captured by this method and the result gives an insight for further reservoir characterization studies such as the unstructured grid blocks.

Introduction

The main objective in describing a reservoir is the characterization of reservoir heterogeneities that influence the flow of fluids through the reservoir. Geostatistical methods are applied in order to integrate geological, geophysical, and petrophysical information to make inferences about static reservoir properties at unsampled locations. These reservoir models can then be used in a variety of ways, such as serving as a common database for oil in place calculation, flow simulation, well placement optimization, and visualization purposes (Seifert et. al., 1999).

Unstructured grids are becoming more commonly used in flow simulation in order to resolve complex features. Today's reservoir simulators are capable of handling irregular grids such as corner point geometry, hybrid grids and curvilinear grids (Figure 1). Using these kinds of grid will almost certainly introduce different block sizes in the field of study. While local grid refinements near wells and/or fault boundaries provide the required level of resolution for these static reservoir properties, there is an inherent heterogeneity within coarse scale blocks that can be overly homogenized and possibly affect the dynamic response of the reservoir. There is a need to capture the heterogeneity of irregularly-shaped multiscale blocks, particularly if coarse scale blocks encompass multiple facies or even multiple sequences.

Conventional reservoir modeling permits heterogeneity characterization of different aspects of the reservoir and involves several modeling tasks. It is common to begin by defining the key structural features, such as relevant horizons and fault block(s). Geological facies distributions between horizons and within fault blocks are then considered. Finally, petrophysical properties, such as porosity and permeability, are then characterized within these defined facies. This is a fairly standard procedure, and assumes that staitionarity of the petrophysical properties is valid within each facies. Geostatistics permits heterogeneity modelin`g within a stationary domain and since the facies model fundamentally defines these stationary zones, we can consider that the petrophysical distribution within a facies is heterogeneously homogeneous. As a result, the facies model which can also be constructed via geostatistics captures a higher (macroscopic) level of heterogeneity (Caers, 2005).

The objective of this paper is to characterize facies connectivity within and between coarse scale blocks. We begin with a brief review of some facies modeling methods, and then propose a methodology that is based on indicator approaches. A small example illustrates the results of applying this approach.

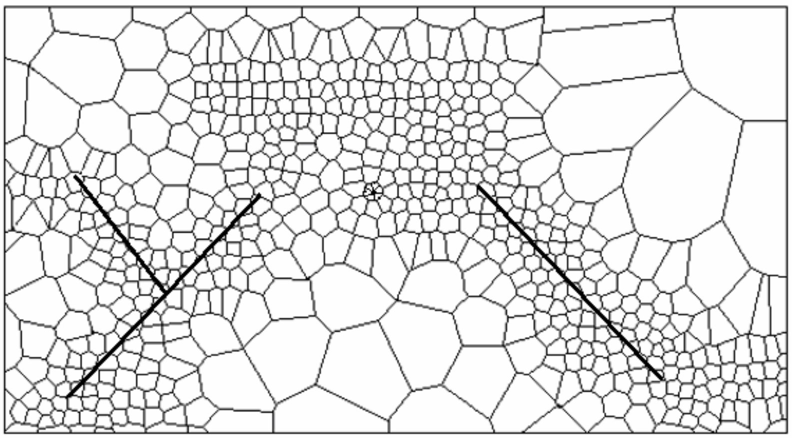


Figure 1. Example of locally refined grid. Grids are refined around wells and faults where pressure and saturation changes are more important. (Source: Castellini, 2001)

Background

The reservoir architecture is represented by heterogeneity modeling techniques. Three main approaches are typical: cell-based modeling, object-based modeling and most recently, multiple point geostatistics using training images. Object-based models are suitable when geobody geometries are well understood and can easily be specified using simple objects. It is primarily a Boolean simulation wherein geo-objects are stochastically populated within the model; the presence of many conditioning wells can be problematic and remains a long-standing challenge to these approaches. Multiple point geostatistics has received much attention recently and relies on extracting multiple point statistics derived from training images. This can yield a realistic geology model, but relies heavily on the training image thus representativity of the image is an important issue. Of the three primary approaches to facies modeling, cell based models remain the most common in practice.

In cell-based modeling, the reservoir volume is commonly discretized into a regular Cartesian grid and relies on the two-point variogram statistic to capture structural correlations. Indicator and truncated Gaussian methods are common in this class of techniques; the former indicator approach is more common in practice. Indicators are widely used in modeling categorical variables because the distribution of uncertainty can be estimated directly (Journel, 1983). The categorical facies data are transformed into a binary variable via the following transform:

$$i(\mathbf{u}_\alpha;k) = \begin{cases} 1, \text{ if facies } k \text{ is present at } \mathbf{u}_\alpha \\ 0, \text{ otherwise} \end{cases}$$

where $k=1,\dots,K$ categories, and $\mathbf{u}_\alpha$ represents a location in domain $\mathcal{A}$. The mean indicator and variance are then defined as:

$$E\{i(\mathbf{u};k)\} = p_k$$

$$Var\{i(\mathbf{u};k)\} = p_k(1-p_k)$$

where p_k is proportion of Facies k within the domain.

Inference using indicators can be performed in one of two modes: estimation and simulation. In the former case, indicator kriging (IK) yields the estimated probability of each threshold at unsampled locations:

$$p_k^*(\mathbf{u}) = \sum_{\alpha=1}^{n} \lambda_\alpha \left[i(\mathbf{u}_\alpha;k) - p_k \right] + p_k$$

where λ_α is the weight assigned to the indicator value at location $\mathbf{u}_\alpha$. In the latter case, sequential indicator simulation (SIS) permits global and local uncertainty to be assessed on the reservoir model (Seifert et. al., 1999). Note that the estimation with indicator results in a continuous attribute (a probability), while SIS results in realizations that consist of categorical values (that represent a specific facies).

Problem Setting

Suppose that a large reservoir model is to be constructed using an unstructured grid. A fine grid is needed in the parts of the reservoir where saturation and pressure changes rapidly such as near wells and faults. However, there is no need to discretize the whole reservoir with a very fine grid and some parts can be discretized by coarser grids (**Figure 1**). This may help to reduce the computational storage, effort and time in flow simulation.

Geologic heterogeneity is not an issue for the fine scale blocks since a sufficiently small block may be adequately characterized by a single facies. As the block scale becomes progressively larger away from wells, these coarser blocks may consist of multiple facies and/or geologic sequences. A geologic description of these coarser blocks must inherently require statements regarding constituent facies proportions; this information, however, is insufficient to capture the facies continuity within and between these coarse blocks. This heterogeneity is important because they may have an impact in the hydrocarbon flow between wells and/or across faults.

Proposed Methodology

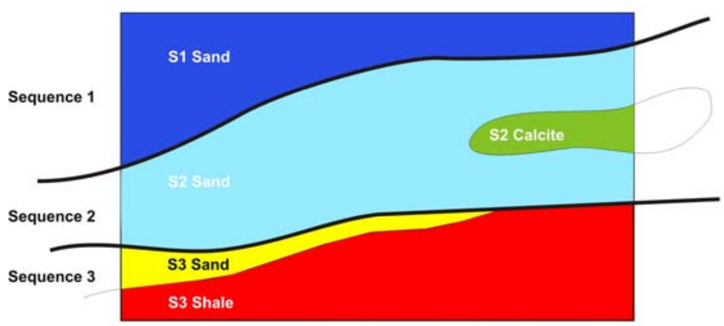
Capturing the heterogeneity in coarse blocks far away from wells necessarily implies that no well information is available about the geology for that localized region. As such, the following methodology is proposed:

1) Perform indicator kriging on the entire field conditioning to the facies data from wells. This yields the local facies proportion at each grid block, and forms the only information available for coarse grid blocks.
2) Refine the geological heterogeneity for a chosen coarse grid block (far from wells) via:
    a. Choose an appropriate fine scale resolution for this grid block.
    b. Perform sequential indicator simulation conditioned on the well data and the local facies proportions from Step (1) above for this refined grid.
    c. Add this locally refined grid simulation to the database and proceed to the next coarse block chosen for selective refinement. Refined simulation of all subsequent coarse blocks will be conditioned on (i) original well data, (ii) local facies proportion for that coarse block, and (iii) any nearby previously refined coarse blocks.

The following section illustrates the results of this algorithm via a small synthetic example. This example considers a simple Cartesian grid for initial testing of the algorithm; a future extension of this application requires the consideration of an unstructured grid.

Example

Consider a field whose extents are 2000 *m* in Easting, 2000 *m* in Northing and 15*m* in vertical resolution (Figure 4). Geological survey shows that there are three different sequences in this field: S1, S2 and S3. Both sequences S2 and S3 are composed of two different facies (See Figure 2).



Categories	Code
Sand in Seq. 1	1
Sand in Seq. 2	2
Lime in Seq. 2	3
Sand in Seq. 3	4
Shale in Seq. 3	5

Figure 2. Schematic illustrations of three different sequences consisting of five facies exist in the field of study and their corresponding codes.

Based on this schematic illustration, a reference model was generated using SIS on the field at a fine resolution with the following variograms for the five different facies:

$$\gamma_1(\mathbf{h}) = 1.0\ Sph_{\substack{ah\_\max=1500 \\ ah\_\min=1000 \\ avert=5}}(\mathbf{h})$$

$$\gamma_2(\mathbf{h}) = 1.0\ Sph_{\substack{ah\_\max=900 \\ ah\_\min=180 \\ avert=5}}(\mathbf{h})$$

$$\gamma_3(\mathbf{h}) = 1.0 Sph_{\substack{ah\_\max=900 \\ ah\_\min=180 \\ avert=5}}(\mathbf{h})$$

$$\gamma_4(\mathbf{h}) = 0.05 + 0.95\ Sph_{\substack{ah\_\max=1000 \\ ah\_\min=500 \\ avert=5}}(\mathbf{h})$$

$$\gamma_5(\mathbf{h}) = 0.05 + 0.95\ Sph_{\substack{ah\_\max=1000 \\ ah\_\min=500 \\ avert=5}}(\mathbf{h})$$

where the $\gamma_i(\mathbf{h})$ is the variogram model corresponding to the i^{th} facies, and *ah_max* is the range in the maximum continuity direction (in this case, north), and *ah_min* is the range in the minimum continuity direction (east), and *avert* is the range in the vertical direction.. For image cleaning purposes, the resulting model was then post-processed using a maximum a-posteriori selection (`maps`) program (Deutsch, 1998). Figure 3 shows 3-D view of reference model.

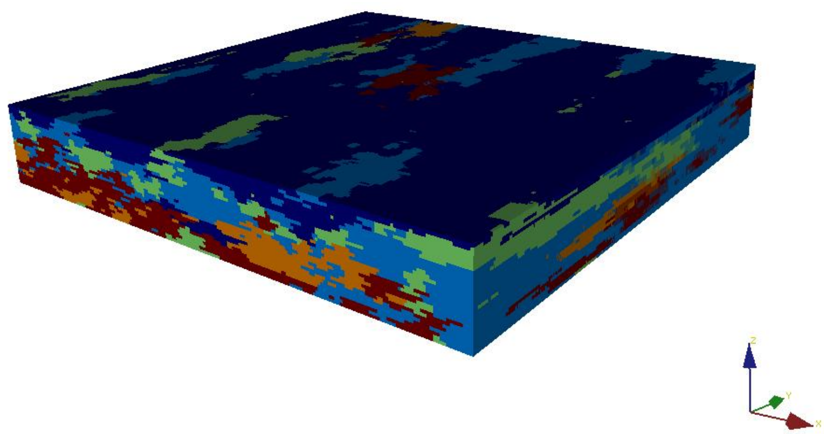


Figure 3. 3-D reference model generated by SISIM.

Suppose that six wells are sampled and the declustered facies proportions are recorded. Figure 4 shows the well locations and the declustered histogram of facies. Using these six wells and the declustered proportions, indicator kriging is performed on the full field for a grid size of 10m in easting, 25m in northing and 15m in elevation (for a total of 400000 blocks).

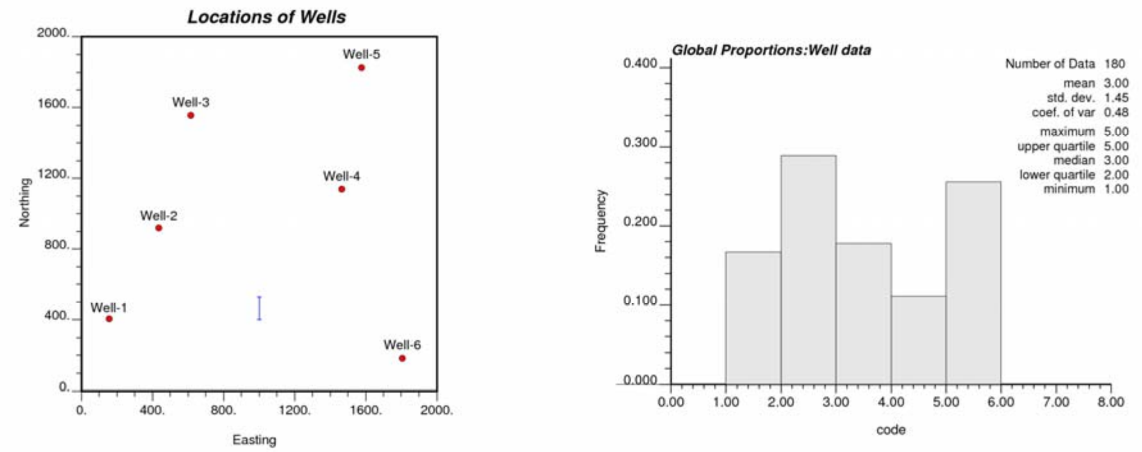


Figure 4. Location of sample wells in the field and (left) and declustered histogram of facies proportions from well data (right).

For the purpose of a refined geological heterogeneity description, five blocks at a northing-elevation cross section is arbitrarily chosen at an Easting of 1000*m* and a Northing between 400 and 525m. This is sufficiently far away from the available wells and little to no local information is available. Figure 5 shows the cross section of the reference model at X=1000 m.

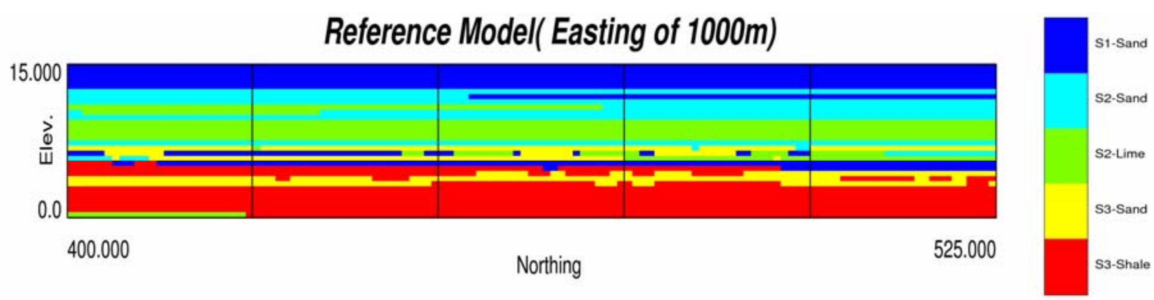


Figure 5. Cross section at easting of 750m showing the five arbitrarily chosen blocks for local refinement of the geology model.

As we proceed with applying indicator simulation for local refinement, two issues are considered for detailed analysis: local grid discretization and the simulation order of the five blocks. For the first issue of grid discretization, we consider simulation of only the first block centered at a northing of 1012.5m. Three different grids are examined (see Figure 6): 50 x 30 cells (for a cell size of 0.50m x 0.50m), 50 x 60 cells (for a cell size of 0.50m x 0.25m), and 100 x 60 cells (for to a cell size of 0.25m x 0.25m). Of the three examined grids, the result with 50 x 60 cells appears to show relatively good agreement with the reference model and is a good compromise between the coarse results of the 50 x 30 cell grid and the noise from the 100 x 60 cell grid. Figure 6 shows simulated and reference block 1 with three different grid sizes.

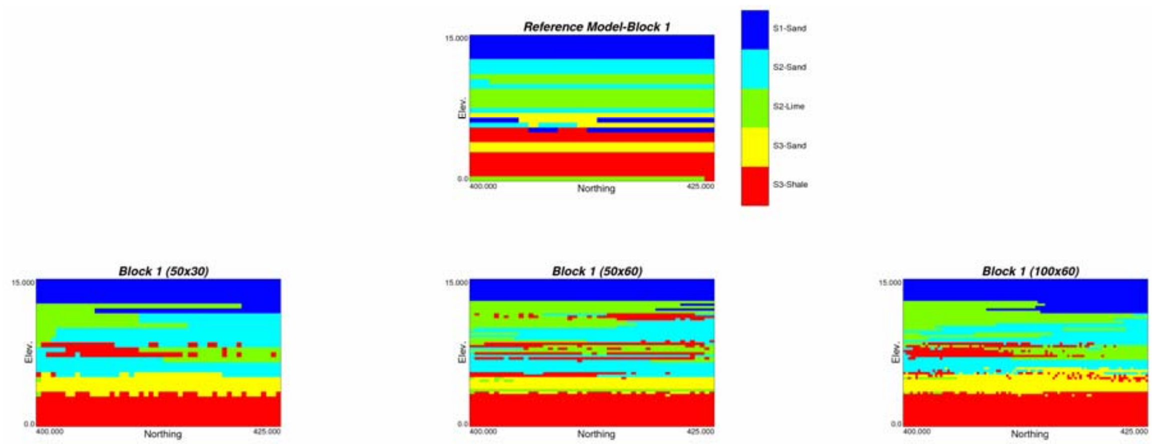


Figure 6. Reference (top) and simulated models of Block 1 (bottom row) at different grid discretizations.

The adjacent block (block 2) is simulated using well data plus simulated values from the previous block. Five connected blocks are simulated sequentially with the same method.

In order to have conditioning data from both sides (not only from left side) another simulation sequences is examined. Block 1, 3 and 5 are simulated with the same method and after that block 2 and 4 are simulated using left and right hand side blocks (block 1 and 3 for block 2 simulation and block 3 and 5 for block 4 simulation) plus the well data. Figure 7 shows the results for five connected blocks with two different simulation sequences. Facies ordering is better reproduced by the first simulation sequence (Left to right) and as we expected category 1 (S1-Sand) and 5 (S3-Shale) lie at the top and bottom with high connectivity.

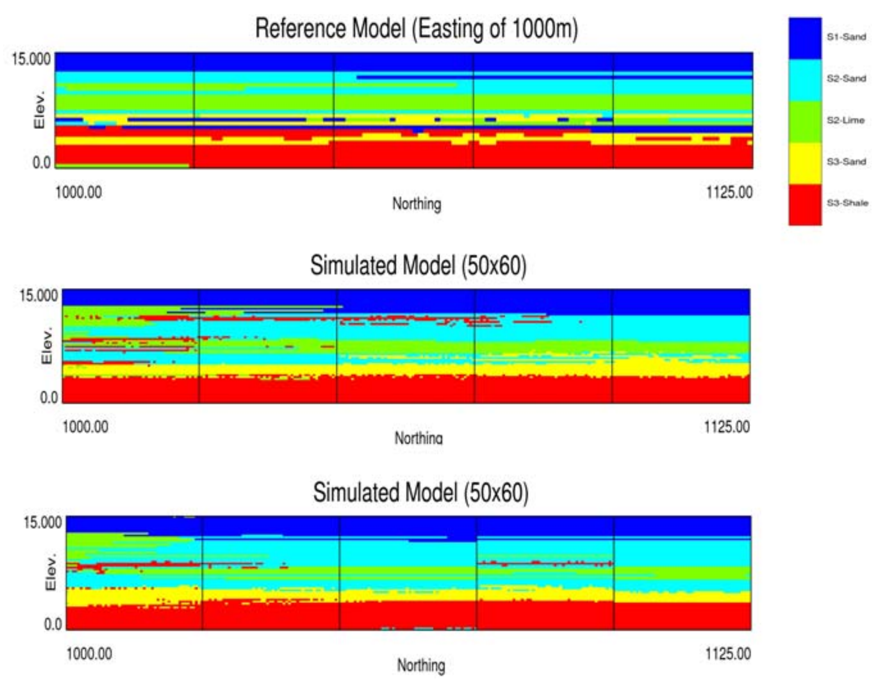


Figure 7. Reference model (top) and five blocks simulated with order from left to right (middle row) and order of 1,3,5,2,4 (bottom row).

Discussion

Modeling the geological heterogeneity and facies is important in reservoir characterization. In the method discussed in this paper, depending on the grid discretization and sequences used in simulation the number of conditioning data increase and this requires more computational time. However this idea is considered for use with large (or coarse scale) blocks and there is no need to implement it on small grid blocks where facies connectivity is not so important. We may consider defining a threshold to determine which grid block(s) should be simulated with this method. Grids with volume greater than the defined threshold are considered for simulation.

Choosing block simulation order is another factor that affects the result. A random order was not examined; however, sequential simulation methods often make use of a random path to avoid artifacts in simulation results. This should be considered for future research.

Facies ordering may be more important in some special cases. Indicator simulation was considered for this study; however, the use of truncated (pluri)Gaussian simulation should improve results where a clear facies ordering is present.

The geological heterogeneity modeled from this study can feed into a simulation of permeability or the calculation of a permeability tensor in regular or unstructured grid (See paper 206 in this report).

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