Geostatistical Techniques Improve Reservoir Management

This is the first of a two-part series on geostatistical techniques. These numerical techniques allow reservoir engineers and geoscientists to create geologically-realistic heterogeneous numerical reservoir models for the determination of volumetrics, well placement and recovery factors. Part 2 of this series will illustrate several field examples.

Geostatistical models and finite difference flow simulations have improved reservoir performance prediction because of their more realistic representation of reservoir heterogeneity. Though geostatistical and flow models are engineering approximations of the actual spatial distribution of petrophysical properties and pore-scale flow processes, the goal of practical reservoir modeling is to capture the geological features that have a first order effect on reservoir performance.

A 3-D numerical reservoir model is the repository for understanding the reservoir architecture and properties. These numerical models could be constructed by simple contouring algorithms. However, knowledge of geological processes and experience with such models indicate the distribution of reservoir properties has greater variability. In particular, flow processes are sensitive to the continuity of extreme high- and low-permeability features, such as fractures or thin discontinuous shales. These features may make up a small volumetric proportion of the reservoir and yet have an overwhelming influence on reservoir performance.

Oil and gas is produced from poorly known subsurface formations. The ability to manage these reservoirs is improved with increased qualitative understanding of the reservoir attributes and then with quantitative numerical models. 3-D numerical geologic models:

- Handle large amounts of geological, geophysical and engineering data.
- Provide consistent analysis and representation of these data in three dimensions.
- Provide direct numerical input to flow simulation and pore volume calculation.
- Test and visualize multiple geologic interpretations.
- Assess uncertainty.

Data integration is a fundamental principle of geostatistics reservoir modeling. The goal is to explicitly account for all available data. Devising techniques that can accommodate a greater variety of data is a large part of the ongoing research in geostatistical reservoir modeling. An abundancy of data exists for reservoir modeling. Some of the data considered are:

- Well log data (surface tops, rock type, porosity Φ, permeability k) by zone.
- Core data (Φ and k by rock type) by zone.
- Sequence stratigraphic interpretation and layering (a definition of the continuity and trends within each layer of the reservoir).
- Trends and stacking patterns available from a regional geological interpretation.
- Analog data from outcrops or densely drilled similar fields (size distributions, measures of lateral continuity).
- Seismic-derived attributes (vertically averaged rock type proportions and porosity).
- Well test and production data (interpreted k-thickness, interpreted channel widths, connected flow paths, barriers).

The uncertainty in the distribution of rock properties is significant because this information is sparse relative to the size of the heterogeneities being modeled. Numerical models of

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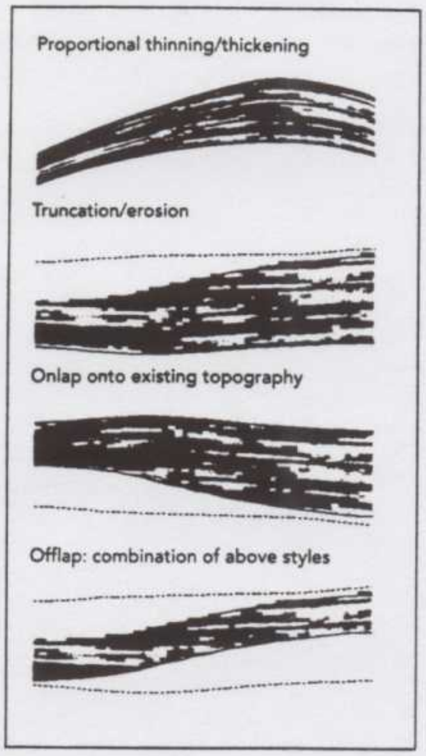

Fig. 1. Four common correlation classifications are used to establish the main directions of continuity within each reservoir layer.

the reservoir lithofacies and rock properties must be constructed to honor the available data. By considering multiple realizations, each consistent with the available information, the uncertainty in the spatial distribution of reservoir properties and the reservoir response to various actions and production schemes can be quantified.

This is not a new concept. Stochastic models of physical systems are used extensively in many scientific disciplines. The ability to assess the uncertainty in the reservoir response to various actions will allow better, risk-conscious reservoir management.

Staged Approach To Modeling

The specific 3-D modeling process used will depend on the data and the time available, the type of reservoir and the skills of the people. A 3-D reservoir model is an array of geological modeling cells (typically no more than 100 million) that discretize the reservoir into relatively coarse cells. Each cell is assigned a dominant lithology, an average porosity, effective horizontal permeability and effective vertical permeability. In many cases vertical permeability is taken as some ratio of horizontal permeability. The areal and vertical extent of the model is established from the size of the reservoir being modeled. The vertical resolution of the geological modeling cells is chosen small to capture important vertical flow effects. Ideally, the areal cell size would be chosen small enough to capture horizontal heterogeneities. Due to computer limitations the horizontal cell size is commonly chosen between 100-1,000 ft.

The reservoir model is filled by breaking the reservoir into major, chrono-stratigraphically correlated reservoir layers. This layering also attempts to keep geologically "homogeneous" rock together. Each layer or zone is modeled independently and the layers are later merged. An important step in the process is to establish the stratigraphic correlation structure or main directions of continuity within each reservoir layer. The four common correlation classifications are proportional, truncation, onlap and offlap (Fig. 1).

A layer-specific, stratigraphic vertical coordinate is defined to restore the main direction of continuity and to undo the offsets at major fault locations. The problem then is to assign lithofacies, porosity and permeability in a regular 3-D Cartesian coordinate system. The lithofacies may be coded as a categorical variable and often as a binary variable, e.g., sand-shale, limestone-dolomite, cemented-noncemented. Porosity and permeability are continuously varying properties assigned on a by-lithofacies basis and merged. Geostatistical techniques for modeling these categorical and continuous properties depend on a quantitative measure of spatial variability.

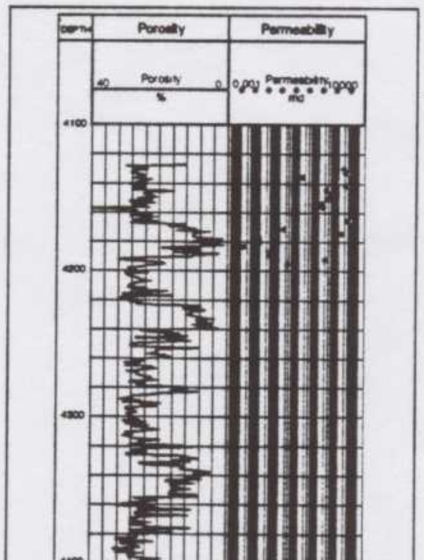

Fig. 2. For a profile of vertical porosity values a limited number of permeability values exist.

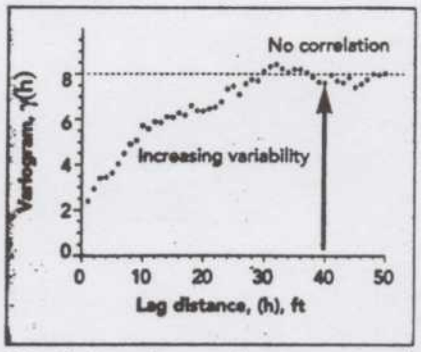

Fig. 3 A variogram is a measure of geological distance in the reservoir specific to the field under study.

The Variogram

The essential contribution of geostatistical techniques to reservoir modeling is the recognition and use of spatial correlation. For historical reasons, geostatisticians use the variogram rather than the more conventional autocorrelation function to quantify spatial dependence. The variogram replaces the Euclidean distance, h, by a structural distance, $\gamma(h)$, that is specific to the attribute and the field under study. The variogram distance measures the average degree of dissimilarity between an unsampled value and a nearby data value.

The porosity variogram for lag distance h is defined as the average squared difference of porosity values separated approximately by h:

$$\gamma(h) = \frac{1}{N(h)} \sum_{N(h)} \left[\Phi(u)-\Phi(u+h)\right]^2$$

Where:

$N(h)$ = The number of pairs for lag h
$\Phi(u)$ = The porosity at location u.

Fig. 2 shows a vertical profile of

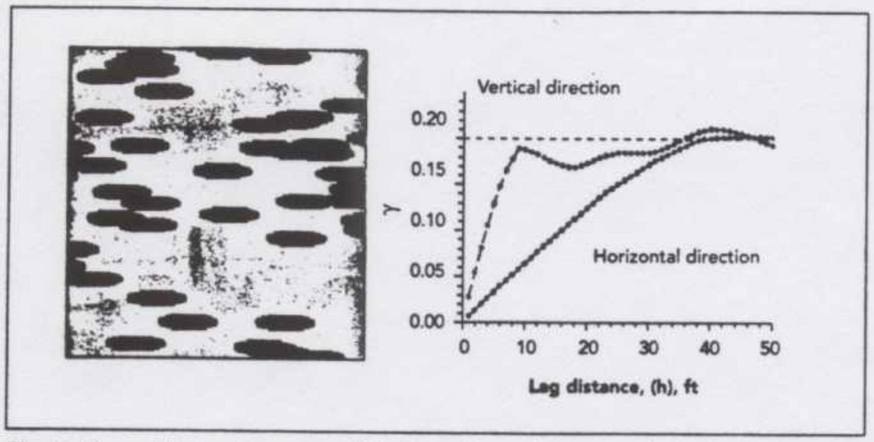

Fig. 4. The vertical variogram, which depends on direction, climbs faster than the horizontal variogram.

porosity values and a limited number of permeability values. The variogram for the porosity values is shown in Fig. 3. The variogram can be thought of as a measure of geological distance, $\gamma(h)$, vs. actual distance, h, in the reservoir. From Fig. 3 the following interpretation can be made.

- The total variability of 8% is the variance of the porosity data. This value is known as the sill.
- Short scale geological variability that explains 2/8=25% of the variability. This value is sometimes referred to as the nugget effect.
- At large distances (greater than 30 ft) there is no more spatial correlation and the geological variability ceases to increase. This distance is known as the variogram range, or range of correlation.

Fig. 4 illustrates the directional variograms in the case of an idealized lithology model. The black ellipsoidal objects represent shale remnants within a sandstone matrix. The variogram was calculated on an indicator variable $i(u)$ set to 0 in sandstone and 1 in shale. Note that the variogram depends on direction, and that the vertical variogram climbs faster than the horizontal variogram.

It is often straightforward to infer the down-well variogram from dense sampling. The variogram in other directions, particularly in the horizontal direction from vertical wells, is often poorly defined. There are some extraordinary cases with tens to hundreds of wells where the variogram may be inferred in all directions from the available data. Horizontal wells can provide an excellent source of closely spaced measurements in the horizontal direction. In other cases a horizontal variogram with little support from experimentally calculated points must be picked.

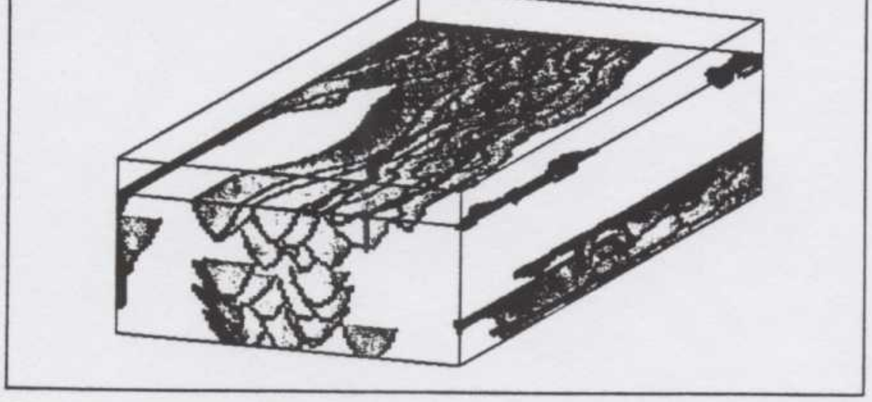

Fig. 5. In an object-based categorical lithofacies codes are assigned using well-defined geological objects.

Experience indicates that the horizontal variogram has a range of continuity 50-500 times greater than the vertical range of correlation. The horizontal-vertical anisotropy in fluvial and estuarine reservoirs will have a 50:1 ratio, and the anisotropy in carbonate reservoirs would have a 500:1 ratio.

The variogram theme has many variations. The traditional variogram described above is the most common. The challenge of stochastic simulation is to fill a 3-D array with lithofacies, porosity and permeability values. A few key algorithms have many variations.

Stochastic Simulation For Lithofacies

Two classes of methods assign categorical lithofacies codes—object-based or cell-based.

As the name implies, object-based are appropriate when geometrically-clear well-defined geological objects exist. Fig. 5 shows a realization of an object-based simulation. The dark colored voxels represent the base of the sand-filled channels. These models are constructed by placing objects within a background matrix following certain size distributions, a target net-to-gross ratio and well data.

The cell-based method used most widely is sequential indicator simulation (SIS), an approach based on an indicator coding of the lithofacies data:

$i(u_\alpha; k) = 1$ if lithofacies k is present at location u_α.
$= 0$ if k is not present.

Where:

k = The integer-coded lithofacies
u_α = The location vector of data number α 1.
$i(u_\alpha; k)$ = The indicator variable.

The SIS algorithm allows filling a 3-D array with indicator variables to honor local well data, global proportions and indicator variograms defining spatial continuity. The popularity of the SIS algorithm is due to its simplicity and ability to honor different types of data.

The SIS algorithm may be described by the following four steps:

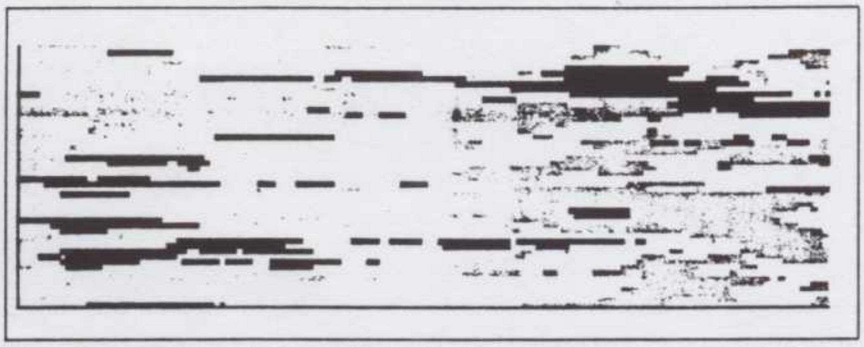

Fig. 6. The sequential indicator simulation algorithm for filling a 3-D array is simple and versatile in its ability to handle different types of data.

- Assign the well data to the closest cell.
- Establish a random path to visit all of the cells.
- Visit each uninformed cell to:
  - Find nearby cells that have been informed either earlier in the random path or by well data.
  - Estimate the probability of each lithofacies at this cell location.
  - Draw a simulated value from the conditional distribution.
- Check the results.

Fig. 6 shows a cross section through a 3-D model created with the SIS algorithm. In this case the dolomitic (dark color) facies have a greater anisotropy than the sandy facies.

Stochastic Simulation For Porosity

The sequential Gaussian simulation (SGS) algorithm is commonly used to build the 3-D porosity model. This algorithm is analogous to the SIS algorithm except that the lithofacies probabilities are replaced with a Gaussian distribution defined by a mean and variance determined by the nearby porosity data.

Although this algorithm works with the mathematically-friendly Gaussian or normal distribution, the histogram of the porosity data need not follow a Gaussian distribution. They can, instead, be easily transformed to a Gaussian distribution for SGS and then retransformed.

Stochastic Simulation For Permeability

Special considerations must be made when modeling absolute permeability. Extreme high and low values have a great impact on fluid flow and the spatial correlation (variogram) is important (for the same histogram, a salt-and-pepper distribution vs. a highly stratified distribution present widely different flow behavior). Also there are fewer permeability data than porosity data available. Permeability is correlated with porosity by building the Φ-model first and then building the k-model in a way that honors this correlation.

For example, consider the problem of assigning permeability to every foot interval in the well illustrated in Fig. 2. The data necessary to address the permeability prediction problem, aside from geological knowledge of the lithofacies types, are the profile of porosity values, the porosity-permeability cross plot and the permeability variogram. The cross plot and variogram are constructed with all available core data. Six cored wells were used for the display in Fig. 7.

The variability in the cross plot is not measurement error but an intrinsic property of porous media. Permeability depends on porosity, grain size, sorting and other factors. The spatial variability measured by the variogram is also an intrinsic feature of porous media. The physical and chemical processes that control permeability also impose the feature that locations close together have more similar permeability than locations far apart.

Rather than a sequential algorithm like SIS or SGS, the permeability prediction problem can be treated as an optimization problem. Two objective functions can quantify the consistency between a realization and the calibration data. Cross plot consistency can be quantified by defining porosity-permeability classes and comparing the fraction of calibration data in each class to the fraction of the realization points in each class:

$$O_1 = \sum_{\substack{\text{all} \\ \text{classes}}} \left[f^c_i - f^r_i \right]^2$$

Where:

f = Fraction or proportion.
c = Calibration.
r = Realization.

Variogram consistency can be quantified by measuring the deviation between the calibration variogram and the realization variogram:

$$O_2 = \sum_{\substack{\text{all} \\ \text{classes}}} \left[\gamma^c(h_i) - \gamma^r(h_i) \right]^2$$

O_2 is the sum of the squared vertical separation between the black dots and the line on the right side of Fig. 8.

The concept is to turn the permeability prediction problem into an

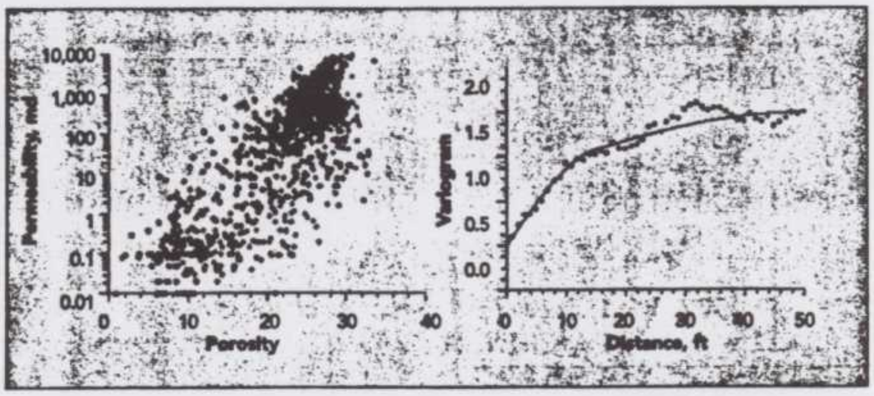

Fig. 7. The profile of porosity values, the porosity-permeability cross plot and the permeability variogram for permeability prediction are constructed from core data.

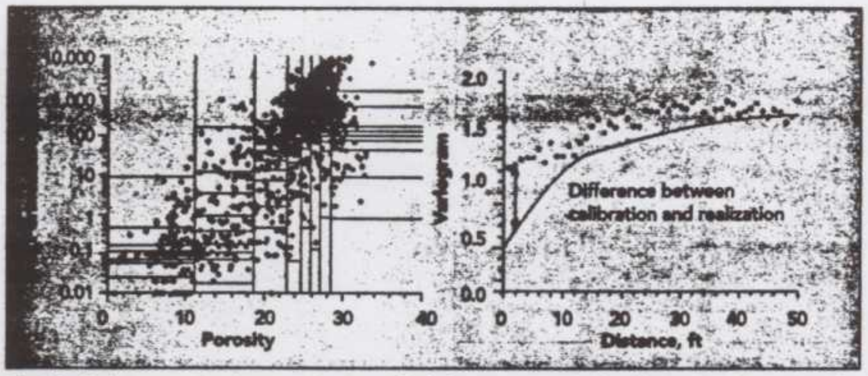

Fig. 8. Variogram consistency is quantified by measuring the deviation between the calibration variogram and the realization variogram.

optimization problem with the objective function being the weighted sum of O_1 and O_2. The technique of simulated annealing is used to solve this optimization problem with the following steps.

- Establish an initial permeability realization that honors the core data, i.e., assign a permeability value to each location by drawing from the cross plot given that location's porosity.
- Calculate the initial objective function, O_1 and O_2.
- Randomly choose a non-data location and consider perturbing the permeability to a new value by drawing from the cross plot.
- Evaluate the new objective function. If it has decreased then accept the change.
- Stop if the objective function is close to zero. Otherwise go to the previous step and continue the perturbation process.

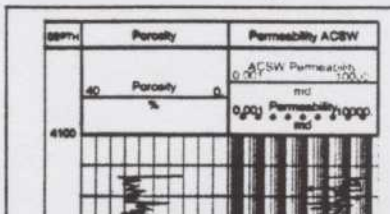

Fig. 9. Permeability realization is the result of multiple perturbations of an initial permeability that honors the core data.

Normally, the number of attempted perturbations is 10-100 times the number of locations. Fig. 9 shows one permeability realization for the example problem. Fig. 10 shows the reproduction of the cross plot and variogram. Conventional techniques such as regression-type transforms or statistical techniques that disregard spatial correlation do not honor the available data as well as the results shown here. This approach is applied for 3-D modeling of permeability once the 3-D porosity model has been constructed.

The simulated annealing-based method for permeability prediction offers many advantages. It accounts for correlation with porosity, honors observed patterns spatial variability and provides the possibility of integrating more complex data, such as well-test derived properties.

Conclusions

- Reservoir management decisions are improved when geologically-realistic numbers are available.
- A staged or hierarchical modeling approach is appropriate. Large scale features, such as faults and layering, are modeled first and then the detailed distribution of rock properties (lithofacies, porosity and permeability) are added.
- The variogram is a geostatistical tool that relates reservoir-specific geological distance to Euclidean or physical distance.
- Stochastic simulation techniques create realizations of rock property distributions that honor the variogram, well data and seismic data.
- Uncertainty may be measured by processing multiple realizations.

The geostatistics usage will grow for several reasons, because academia has become less dogmatic about the theory and mathematical notation underlying geostatistics, an increasing number of practical examples are available to support geostatistical techniques and customer demand has prompted commercial software vendors to include geostatistical tools in integrated and easy-to-use programs.

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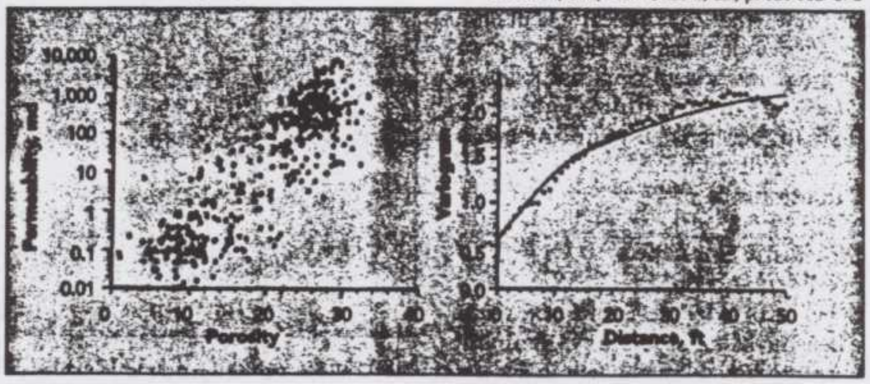

Fig. 10. Techniques that disregard spatial correlation do not honor all the available data.

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