
25 Geostatistical Simulation and Reconstruction of Porous Media

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25.1 INTRODUCTION

An important problem in the modeling of large-scale porous media, such as oil, gas, and geothermal reservoirs, and the simulation of fluid flow therein is the identification of the flow paths that consist of the interwell zones with significant permeabilities. Kriging (Jensen et al., 2000; Sahimi, 2011) has been used for many years for extrapolating the existing data to the interwell regions. But Kriging produces permeability and porosity fields that are excessively

smooth (Journel and Deutsch, 1993; Goovaerts, 1997; Jensen et al., 2000; Sahimi, 2011) with the consequence that the low and high property values are under- and overestimated, respectively. Hence, Kriging estimates are not suitable for representing highly structured systems, such as heterogeneous aquifers and oil and gas reservoirs, and predicting fluid flow through such porous formations. For example, the shortcomings of Kriging become clear when one tries to predict the water breakthrough in an oil reservoir in various flow regimes, because in the Kriging approach, the subsurface connectivity and variability cannot be reproduced with enough resolution to be useful in practice.

Another main shortcoming of Kriging-based geostatistical modeling is its inability for reproducing complex patterns. The main reason is that such methods consider only two-point statistics, hence limiting the order of the complexity that can be reproduced, if higher-order statistical properties are considered, computed, and analyzed, or data for them are available. Over the last two decades, the need for developing methods that can make simultaneous use of many points has been emphasized. Therefore, many alternative methods have been proposed.

Some of such alternatives are based on stochastic or geostatistical simulations, which have been developed to overcome the problems associated with the smoothness problem (Matheron, 1973; Journel, 1974; Journel and Huijbregts, 1978; Jensen et al., 2000; Sahimi, 2011). Stochastic methods generate many realizations of a porous medium that reproduce the broad heterogeneity and spatial uncertainty in the medium's properties (Caers, 2005; Sahimi, 2011). Multiple realizations allow assessing the uncertainty and quantifying it accurately. Due to such a distinct advantage, geostatistical simulations are used frequently in mining, reservoir modeling, and hydrogeology.

Several stochastic methods have been proposed that are based on variograms. They include sequential Gaussian simulation (SGSIM) and sequential indicator simulation, which have been popular and used extensively. Their main difference with Kriging is that stochastic simulations reproduce the spatial heterogeneity that the variograms represent, whereas Kriging aims only at determining a unique estimate by minimizing the error's variance, which is smooth.

In general, geostatistical methods may be grouped into three main classes. In one group, there are object-based simulation methods that consist of marked point process (Kleingeld et al., 1997), and the Boolean method in which a porous medium is represented as a collection of independent stochastic objects whose geometries are based on a specific statistical distribution (Haldorsen and Damsleth, 1990; Deutsch and Wang, 1996; Holden et al., 1998; Skorstad et al., 1999).

Pixel-based methods belong to the second group. They are based on defining an array of points or pixels in a regular grid (Goovaerts, 1997; Deutsch and Journel, 1998; Chiles and Delfiner, 1999), with the pixels representing various properties of a reservoir.

Such methods as conditional simulations via the lower-upper (LU) decomposition of the covariance matrix (Davis, 1987), the SGSIM (Dimitrakopoulos and Luo, 2004), frequency-domain simulation (Borgman et al., 1984; Chu and Journel, 1993), simulated annealing (SA; Deutsch, 1992; Hamzehpour and Sahimi, 2006; Hamzehpour et al., 2007; Sahimi, 2011), and the genetic algorithm (GA; for a discussion, see Sahimi, 2011) are in the last group. The last two methods are optimization techniques that determine the most plausible realization of a porous medium, given some data.

Each of such methods has some advantages, as well as limitations. For example, object-based simulations are accurate in reproducing geological features, but they require intensive computation and encounter difficulty when one tries to condition the model to dense hard (quantitative) data and integrate them with soft (qualitative) data. Pixel-based simulations work on one pixel at a time and, thus, are accurate for data conditioning, but because they use variograms that represent two-point statistics, they cannot capture complex and curvilinear features of porous media and, thus, fail when the models that they generate are used in the simulation of flow and transport problems in large-scale porous media. In addition, they are usually quite slow.

Such shortcomings have led to the development of more accurate methods, based on multiple-point statistics (MPS) (Journel, 1992; Guardiano and Srivastava, 1993; Srivastava, 1994), which