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Research paper

Comparison of particle swarm optimization and simulated annealing for locating additional boreholes considering combined variance minimization

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ABSTRACT

One of the most important stages in complementary exploration is optimal designing the additional drilling pattern or defining the optimum number and location of additional boreholes. Quite a lot research has been carried out in this regard in which for most of the proposed algorithms, kriging variance minimization as a criterion for uncertainty assessment is defined as objective function and the problem could be solved through optimization methods. Although kriging variance implementation is known to have many advantages in objective function definition, it is not sensitive to local variability. As a result, the only factors evaluated for locating the additional boreholes are initial data configuration and variogram model parameters and the effects of local variability are omitted. In this paper, with the goal of considering the local variability in boundaries uncertainty assessment, the application of combined variance is investigated to define the objective function. Thus in order to verify the applicability of the proposed objective function, it is used to locate the additional boreholes in Esfordi phosphate mine through the implementation of metaheuristic optimization methods such as simulated annealing and particle swarm optimization. Comparison of results from the proposed objective function and conventional methods indicates that the new changes imposed on the objective function has caused the algorithm output to be sensitive to the variations of grade, domain's boundaries and the thickness of mineralization domain. The comparison between the results of different optimization algorithms proved that for the presented case the application of particle swarm optimization is more appropriate than simulated annealing.

1. Introduction

Generally exploratory boreholes are drilled to increase the information and reduce the uncertainty in the decision making phases (Scheck and Chou, 1983). Three-dimensional ore body model is produced according to the information gained from borehole samples and used as one of the principal inputs for mineral resource/reserve evaluation, feasibility study, planning and scheduling studies (De Souza et al., 2004). The basic presumption in the production planning process is that the three-dimensional block model of ore body represent the actual variability of grade in the deposit while these models include uncertainty so all the plans designed accordingly inherit uncertainty. To reduce the uncertainty, the knowledge about the under-study area should be increased so increasing the number of samples by drilling additional boreholes is the simplest and also the first method to be considered. On the other hand uncertainty reduction is proportional to the number of the boreholes and exploratory costs (Froyland et al., 2004). Drilling additional boreholes consumes lots of time and money. The uncertainty is not distributed uniformly (homogeneous) throughout the deposit (Pilger et al., 2001), so the effect from drilling additional boreholes will be a function of new boreholes locations. Designers always seek to simulate the most suitable model (Armstrong et al., 1989; Szidarovszky, 1983) with the least possible number of boreholes due to budget constraints which means optimizing the additional borehole pattern. This problem is usually addressed in two categories: 1) optimally locating the additional boreholes. 2) Minimizing the number of boreholes to be drilled (Soltani and Hezarkhani, 2009). To achieve these goals implementation of Geostatistics alongside operations research optimization techniques could be helpful.

The research on exploratory drilling pattern optimization has been carried out for over four decades (Kim et al., 1977; Scheck and Chou, 1983; Szidarovszky, 1983; Walton and Kauffman, 1982).

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Preliminary studies were designed and handcrafted in a two-dimensional space then have been evolved through time by development of computational algorithms and has been recently replaced by Metaheuristic algorithms. Defining a proper objective function is the necessary step for locating the additional boreholes. Kriging variance is independent from sample values which means that it could be calculated even before sampling based on the sample locations and variogram model parameters (Deutsch, 1996; Silva and Boisvert, 2014). This special feature has made kriging variance minimization as the most popular objective function for these sorts of problems (Gao et al., 1996; Gershon, 1983; Gershon et al., 1988; Saikia and Sarkar, 2006; Soltani-Mohammadi et al., 2012; Soltani and Hezarkhani, 2009; Soltani et al., 2011). However, there are some other functions such as misclassification error (Soltani-Mohammadi et al., 2012; Soltani and Safa, 2015)and realistic value of the information (Soltani-Mohammadi and Hezarkhani, 2013) that have been utilized for defining the objective function.

Although kriging variance is widely used to define the objective function, it is not sensitive to local variability (Goovaerts, 1997). As a result, location of additional boreholes is only affected by primary data configuration and variogram model parameters and is independent of local variability. In spite of kriging variance, parameters like conditional variance (calculated based on the results of sequential Gaussian simulation, sequential indicator simulation and multiple indicator kriging algorithms) (Juang et al., 2004), interpolation variance (Yamamoto et al., 2012) and combined variance (Silva and Boisvert, 2014) are able to provide a proper and realistic analysis of local uncertainty based on configuration and grade values. The combined variance, as a function of kriging and local variances, not only includes spatial configuration and grade continuity but also local variability around the block to be estimated (Arik, 1999a, 1999b; Yamamoto, 1999). In the present study the objective function is defined based on combined variance and its performance for locating the additional boreholes in Esfordi deposit is evaluated using optimization methods such as simulated annealing (SA) and particle swarm optimization (PSO). These methods are quite popular heuristics for solving complex optimization problems. Previously, SA has been successfully used for solving a wide range of optimization problems. This optimization technique acts on the basis of a condensed material behavior at low temperatures, which in fact simulates the annealing process in nature like freezing and crystallizing liquid or cooling and annealing metal (Niknam et al., 2009). PSO is a modern evolutionary computation technique based on a population mechanism (Clerc and Kennedy, 2002). It has been motivated by the simulation of the social behavior of individuals living together in groups. Each individual tries to improve itself by observing other group members and imitating the better ones. This way, the group members are performing an optimization procedure (Kennedy et al., 2001).

2. Quantifying the classification uncertainty of block model

One of the preliminary steps of mineral reserves evaluation is geological modeling or domaining which is carried out on the basis of discrete (presence or absence of lithology events) and/or continuous (grade of elements or minerals) data for 3D delineation of ore body from the surrounding area of waste or other areas with different grade values (Leuangthong and Srivastava, 2012). In conventional methods these domains are constructed by an expert according to the fact that whether the boreholes have intersected the ore body in sections. There is another method in which the grade is estimated in each block individually then all blocks are sorted into mineralized and surrounding waste rocks (or grade domains) categories based on the threshold grade. The risk assessment of the decisions made on the boundaries of these domains necessitates the quantitative evaluation of boundaries uncertainty. Application of indicator kriging method instead of expert-based methods could be considered as an available tool for surveying the boundaries uncertainty. Indicator kriging is a non-parametric geostatistical method for producing probabilistic maps based on binary data (0,1) (Journel, 1983). In this method the variable is converted to an indicator variable, through the following non-linear equation based on the threshold value Z_c for continues variables Z:

$$I(x)=\begin{cases}0, & \text{if}\, Z(x)<Z_c\\ 1, & \text{if}\, Z(x)\geq Z_c\end{cases} \tag{1}$$

or following transformation for categorical variable:

$$I(x)=\begin{cases}0, & \text{if geological feature is present at location } x\\ 1, & \text{if geological feature is not present at location } x\end{cases} \tag{2}$$

Then the experimental indicator semivariogram is calculated and an appropriate model is fitted to it. Afterwards, the probability of exceeding the threshold value (or occurrence of geological feature) in the center of each block $I^*(x_0)$ could be estimated by indicator kriging:

$$I^*(x_0)=\sum_{j=1}^{m}\lambda_j I_k\left(x_j\right) \tag{3}$$

where λ_j representing indicator kriging weights (Van der Meer, 1993). Thus the estimated blocks could be referred as mineralized or surrounding waste rocks by defining a value as the threshold probability (Marinoni, 2003). A range of extensive researches have been carried out to define geological unit boundaries by means of indicator kriging method (Johnson and Dreiss, 1989; Pawlowsky et al., 1993; Perez and Basterrechea, 2007; Tercan, 1998). Estimation variance can be calculated from the following equation (Journel and Huijbregts, 1978; Sinclair and Blackwell, 2002):

$$\sigma_{kv}^2=2\left[\sum\lambda_i\gamma(x_0,x_i)\right]-\sum\sum\lambda_i\lambda_j\gamma\left(x_i,x_j\right) \tag{4}$$

where $\gamma(x_0, x_i)$ is the value of semivariogram between x_0 and location x_i and $\gamma(x_i, x_j)$ is the semivarigram between x_i and x_j. Kriging variance is dependent on the parameters such as ore body features provided by variogram, estimated block size and shape, total number of samples used for block estimation, relative location of the samples in respect with each other and the block itself (Silva and Boisvert, 2014; Yamamoto, 2000) but its value is independent of variable value (Armstrong, 1983; Journel, 1986; Journel and Huijbregts, 1978; Webster and Oliver, 2001). So if the semivariogram is predetermined the estimation error can be calculated for each sampling pattern before the sample collection. As a result it would be possible to design a sampling pattern with a specific level of certainty (Webster and Oliver, 2001). On the other hand being independent of local variability is considered a defect for kriging variance to be applied as an uncertainty criterion (Goovaerts, 1997). In order to correct this defect a criterion should be used that not only possesses the advantages of kriging variance but also be sensitive to local variability.

Combined variance is proposed for the first time by Arik (1999a, 1999b) and Heuvelink and Pebesma (2002). Combined variance (σ_{cv}^2) can be defined as a combination of kriging variance (σ_{kv}^2) and Local variance (σ_{lv}^2) as follows (de Souza et al., 2010):

$$\sigma_{cv}^2=\sqrt{\sigma_{lv}^2\times\sigma_{kv}^2} \tag{5}$$