Risk reduction in Sechahun iron ore deposit by geological boundary modification using multiple indicator Kriging

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Abstract: Uncertainty on the geological contacts and the block volumes of the models along boundaries is often a major part of the global uncertainty of reserve estimation. This work introduces a geostatistical technique that has been developed and tested in an iron ore deposit at Bafq mining district, in central Iran, and that, based on a probability criterion, helps to objectively model the geometry of this iron ore deposit. The main problem in reserve estimation of this ore body is its geometrical modeling and uncertainty in geological boundaries. This work deals with the geostatistical method of multiple indicator kriging, which is used to determine the real boundaries of ore body in different categories. This approach has potential to improve project performance and decrease operational risk. For this purpose, the ore body is separated into two categories including rich iron zone (\(w(Fe) > 45\%\)) and poor iron zone (20\% < \(w(Fe) < 45\%\)). It significantly benefits to decrease the risk of reserve evaluation in the deposit. This case study also highlights the value of multiple indicator kriging as a tool for estimates the position of grade boundaries within the deposit. Comparison of the resultant probability maps with the real ore/waste contacts on the extracted levels shows that the first indicator model could separate the whole ore body (poor plus rich) from the waste zone by probability of more than 0.35, which includes the total reserve of 53 million tons. The second indicator model applied to separate the rich and poor domains and the results show that the blocks with the estimated probability of equal to or more than 0.4 lay within the rich ore zone consisting of 15.8 million tons reserve.

Key words: geological boundaries; multiple indicator kriging; risk assessment; block model uncertainty; Sechahun deposit

1 Introduction

The generation of geological models always goes along with lithological and mineralogical domains, and should represent the estimator’s best knowledge of the genesis of the deposit.

A number of techniques exist for boundary modeling and some developments for reducing the uncertainty near boundaries are currently applied. A brief review is provided here; however, the subject is vast and encompasses many case studies. Based on a probability criterion, in some cases, indicator kriging methods help to objectively model the geometry of geological zones \([1−3]\); LARRONDO and DEUTSCH \([4]\) used a linear model of coregionalization (LMC) to simulate grades using data from adjacent rock types; there are different approaches to estimate the grades within geological domains using kriging approaches and simulation \([5−7]\), presenting a number of techniques specific to model geology zones with soft boundaries; the potential field method to build 3D geological models \([8]\) and interpretations from the geologist \([9]\).

However, no specific method highlighted a methodological framework able to guarantee a correct and efficient structural analysis, necessary for getting the best estimation of grade distribution in case of transitional boundaries in complex geological deposits.

The resource evaluation of an iron ore deposit is often performed in three steps: 1) delimitation of the boundaries of the units corresponding to the various geological formations or ore types; 2) estimation of grades within each unit; and 3) estimation of densities. In simple cases (e.g., a series of sub horizontal layers), the geometric model can be built using 2D geostatistical techniques (kriging or cokriging of the elevations or thicknesses of the various horizons) which also quantify the uncertainty of the model. A recent work by OSTERHOLT et al \([10]\) shows these steps. A lot of efforts have been undertaken to develop 3D modeling tools capable of handling more complex situations \([11]\). When assessing resources, knowledge of the degree of uncertainty of the estimation is as important as the estimate itself. Uncertainty on the boundaries and
volumes of the various units is often a major part of the global uncertainty. The potential field method [8] was designed to build 3D geological models from data available in geology and mining exploration, namely: 1) a geological map and a digital terrain model (DTM); 2) structural data related to the geological interfaces; 3) borehole data; 4) gravity data; and 5) interpretations from the geologist [9].

This work introduces a geostatistical technique that has been developed and tested in an iron ore deposit at Bafq mining district, in central Iran, and that, based on a probability criterion, helps to objectively model the geometry of this iron ore deposit. Reducing the uncertainty in ore-body boundaries, which discriminate ore from unmineralized waste is a beneficial tool to risk reduction in this deposit. Categorical boundary separation is a vital matter in this mine especially in exploitation stage for discrimination between run of mine direct ship (w(Fe)>45%) and processing plant feeds (w(Fe)<45%).

2 Sechahun iron ore deposit

Sechahun iron deposit is located 50 km northeast of Bafq and 170 km east of Yazd in central Iran. Figure 1 shows the location of the Sechahun iron ore mine which consists of anomalies X and XI. Anomaly X crops out as some small black hills containing about 14 Mt iron ore reserve (mainly rich magnetite ore). The main ore body of Sechahun (anomaly XI) is blind, covered by conglomerate, young terraces, and gravel fans. This deposit has been explored by geophysical methods and extensive drilling. The deposit is divided into two parts (north-XI and south-XI ore bodies) with a total reserve of about 140 Mt iron ore with an average grade of 36% Fe. The mine is designed on the basis of two separate open pits (north and south pits). The south pit applies selective mining method, and due to thick overburden, the north pit has a relatively high stripping ratio. The mineable reserve of the Sechahun deposit (both pits) has been classically estimated to be 106 Mt with a stripping ratio (W/O) equal to 2.48/1. South ore body is much geologically complex and discrimination between boundaries is so sophisticated.

3 Geology of Sechahun ore body

Each anomaly consists of two or three tabular to lens shaped main ore bodies, in association with many other smaller lenses. The mineralization is hosted by altered rhyolitic tuff and intercalated shallow-water sandstone, dolomitic limestone and shale, representing the middle succession of the Saghand Formation [12]. The deposit shows a spectrum of mineralization style which ranges from massive ore bodies and metasomatic replacements to local vein and stockwork systems. Although the main iron mineral is magnetite, all gradations towards hematite (martitization) can be recognized. The volcano-sedimentary host rocks have been pervasively altered and the original chemistry of these rocks is strongly modified by metasomatic alteration. These strongly altered rocks which are locally named metasomatite are widespread at the deposit and show a gradual transition toward poor iron ore. The host rocks and the ore bodies are crosscut by E–W and NW–SE trending normal faults. In addition, late E–W-oriented, unaltered dolerite and dioritic dikes locally crosscut the ore bodies and the alteration [13].

Based on previous studies and documents, the different types of Sechahun iron ore are: 1) High-grade magnetite or rich iron ore (w(Fe)>45%); 2) Oxidized high-grade magnetite (hematitized); 3) Low-grade magnetite or poor iron ore (w(Fe)<45%).

4 Indicator kriging

Indicator kriging is a kriging analysis performed on a binary-transformed sample population. This approach
firstly proposed by JOURNAL [14] can be used if the spatial correlation of a highly variant parameter is difficult to describe by the raw data. Other useful applications are the modeling of categorical variables, e.g., if a sample belongs to a certain rock type, or if a variable lies above or below a defined cutoff value [15]. Defining indicators for categorical variables would lead to the following transformation:

\[
i(x, \text{grade}) = \begin{cases} 
0, & \text{if } z(x) \leq \text{cutoff} \\
1, & \text{if } z(x) > \text{cutoff}
\end{cases}
\]

where \(i(x, \text{grade})\) is the indicator transform at location \(x\) depending on the presence of a specified grade, and \(z(x)\) is the observed categorical realization at location \(x\).

Every mining project requires defining the mineral resources prior to mine design and planning. This definition is based on geological knowledge of the ore body and on sample information from an exploration drilling grid, usually, with infill drilling in the areas to be extracted during the first years of the project. The first step in resources estimation is an exploratory analysis aimed at understanding the characteristics of the available data and identifying homogeneous geological domains within the deposit, according to the spatial continuity of grades and the geological features such as lithology, mineralogy and alteration.

The practice of IK involves calculating and modeling indicator variograms (that is, variograms of indicator-transformed data) at a range of cut-offs or thresholds which should cover the range of the input data. This approach is termed multiple indicator kriging (MIK) [15].

5 Input data for geostatistical modeling

Once the geological model is as complete as the available data and knowledge of the setting and genesis of the mineralization allow, the data must be coded according to its domain. Hopefully, the geological modeling will have highlighted a number of domains, which should conform in some way with the geology wherever possible. It is obvious that in the geostatistical approaches, the increasing of the data will significantly enhance the accuracy of estimation which consequently reduces the risk of assessment. In this case, the grade modeling is constrained entirely by the geological modeling, and the resource grade model will be a true reflection of the geology. Domains may be defined by a combination of statistical and geostatistical means, in addition to or instead of by a cut-off grade [16].

As the result of metasomatic replacement of host rock by iron-rich hydrothermal fluids [6], the geological boundaries in this case are gradual or soft boundaries, requiring much more careful treatment when estimating. Statistical analysis may help decide the nature of the domain boundaries. The analysis should include studies of how grades change at domain boundaries.

The 3D model of Sechahun iron ore has constructed by drill holes at 50 m average core drilling spacing and also a 3 m x 4 m blast hole data set from 11 benches within the open pit. All samples were composited to 2.5 m down the hole lengths. Totally, it comprises 39597 composited data consisting of exploration boreholes and blast holes from excavated levels. However, in the cases with insufficient data set, it is possible in the proposed methodology to develop the data set by coding the waste zones and adding them to the samples. This is a beneficial approach increasing the certainty of the estimation particularly near the complex boundaries. Figure 2 presents the spatial grade distribution of the Fe concentration for total database separated into poor and rich grade category.

6 Geological model constrain

Prior to grade estimation, it is necessary to construct the geological model and/or the domain model, usually three-dimensional, representation of the volume of mineralization to be estimated. This is usually a semi-automatic process, but generally requires a confining shape in which to generate the blocks. The Sechahun geological ore model is given by a three-dimensional enclosed solids (poor and rich constraints). These are generated by wire framing strings of points on section, and by a series of points (blast holes of excavated benches) and strings into a digital terrain model, more commonly termed a surface (Fig. 3).

Finally, the ore zones DTM have been constructed according to mineralization domains for the usual ordinary kriging (Fig. 4).

Three problems arise during this process: The definition of geological domains relies on the subjective interpretation of the mining geologist and on his understanding of the genetic processes that causes the mineralization. Various interpretations are therefore possible. The delineation of the geological domains is always subjected to errors, since only fragmentary information is available through a finite set of samples drilled in the deposit. Delineating the domains must be done carefully, accounting for geological knowledge about the deposit genesis. Alternatively, one could consider modeling the uncertainty in the boundaries layout by resorting to a geostatistical simulation technique. The boundaries that define the contact between adjacent geological domains are seldom “hard”, that is, the grades measured at either side of a boundary are not independent. Besides, the boundary may be defined by a change in the local mean grade, which is
Fig. 2 Histogram of Fe concentration (%) for total data set demonstrating two different grade populations separated into poor and rich iron ores.

<table>
<thead>
<tr>
<th>Anderson-darling normality test</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>A-squared</td>
<td>905.98</td>
</tr>
<tr>
<td>P-value</td>
<td>0.005</td>
</tr>
</tbody>
</table>

| Mean | 39.095 |
| Stdev | 15.148 |
| Variance | 229.469 |
| Skewness | 0.17306 |
| Kurtosis | -1.30195 |
| N | 39597 |

| Minimum | 0.010 |
| 1st quartile | 25.3710 |
| Median | 36.440 |
| 3rd quartile | 53.920 |
| Maximum | 69.760 |

95% confidence interval for mean 38.946 to 39.245
95% confidence interval for median 36.190 to 36.720
95% confidence interval for StDev 15.043 to 15.254

Fig. 3 Geological cross section illustrating use of bore holes and blast holes in 3D geological modeling.

Fig. 4 Geological model in 3D indicating poor zone (orange) and rich zone (red).
usually gradational rather than abrupt. Normal practice is to estimate the grades and assess the mineral resources within each geological domain independently [17].

7 Modeling with indicator kriging

Once several series of coherent domains have been defined, the numerical characteristics of the mineralization in each of these areas should be described. It is easy to imagine that geological characteristics that were formed in a slow geological environment are better correlated to each other than if they were results of an often abruptly changing geological process. The power of kriging results from the fact that, as a preceding step to the interpolation between the known observation points, a structural analysis of the spatial correlation revealing details of the geological forming process has to be performed.

The most common geostatistical tool to model the spatial correlation is the variogram. Indicator kriging can be performed at several cutoffs using a separate variogram model for each cutoff (Figs. 5 and 6). Variograms reveal important details of the geological generation since they provide an analytical means to quantify the anisotropy and the range of the underlying forming process. To speak in statistical terms, variograms quantify the distance (range) at which samples become uncorrelated from each other and they give an idea of the direction of the best and worst spatial correlation. Having established a model of the spatial correlation, the next step in a kriging analysis is the definition of an estimation grid that is put over the study area.

Assuming a cutoff grade of 20% for the first and a cutoff grade of 45% for the second ore zones, respectively, all the composites data are converted to 0 or 1 using indicator transformation function. Then, MIK applied to the transformed data and the probability number was calculated for each block. Table 1 presents the fitted indicator variogram exponential model parameters to be used in indicator kriging modeling in two different cut off grades.

Table 1 Specifications of directional variograms at higher continuity direction for two different cut off grades

<table>
<thead>
<tr>
<th>Cutoff grade/%</th>
<th>Variogram model</th>
<th>Azimuth</th>
<th>C₀</th>
<th>Sill</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>Exponential</td>
<td>112</td>
<td>0.046</td>
<td>0.11</td>
<td>110</td>
</tr>
<tr>
<td>45</td>
<td>Exponential</td>
<td>157</td>
<td>0.049</td>
<td>0.12</td>
<td>88</td>
</tr>
</tbody>
</table>

The multiple indicator kriging technique was developed to calculate the cumulative tonnage above each cut-off. The three-dimensional indicator kriged models illustrate the distribution of the iron content probability within the ore body after taking two cut-off grades.

8 Defining probability thresholds

Having performed an indicator kriging analysis, suitable visualization software is needed to depict the kriged model outcome at the estimation grid points at various probability thresholds. It is then up to the geologist to judge, which model probability represents best the reality [18]. In order to distinguish the poor/waste and the rich/poor contacts in Sechahun deposit, the estimated probability map of each previous extracted bench is overlaid to the real ore boundary of the same bench obtaining from blast holes iron analysis. Figures 7 and 8 show the estimated and real ore boundary in level 1585 m of the Sechahun open pit on the basis of poor and rich grade categories, respectively. As it is clear from these figures, there is a good conformity between estimated and real ore/waste and poor/rich contacts of the ore body. By applying this index to the unexploited levels (1550 to 1400 m), the actual contacts for the remaining ore body have been estimated.

To test the accuracy of the proposed method,
correlation diagrams of estimated data are plotted versus blast holes data from new excavation levels of the deposit. The solution to reduce the risks of kriging estimations in complex geological models is verified with comparisons of ordinary kriging (OK) and a combination of indicator kriging and ordinary kriging (IK-OK). In the former method, the geological modeling is used by only geology interpretations and then by ordinary kriging, and in the latter, after using multiple indicator kriging and identifying the appropriate threshold, Fe variability is estimated by ordinary kriging. As an example, the comparison between estimated iron ore and real grade variability in the blast holes using the mentioned methods are demonstrated in Figs. 9 and 10, respectively.

Comparison of the correlation coefficients of both diagrams indicates that in the deposits with the complex geometrical boundaries additional approaches such as multiple indicator kriging can rigorously reduce the risk of boundary uncertainty

9 Conclusions

1) The studies completed for indicating the Sechahun iron ore boundaries provide an illustration of some of the difficulties that emerge when estimating recoverable resources for poor and rich ore zones
especially near the grades measured at either side of boundaries. The challenge is to provide estimates to develop the geological model and compare with traditional geological constraints.

2) Multiple indicator kriging for iron grade as the main variable is shown to be a viable approach to the estimation of poor and rich resources in the Sechahun deposit, especially when the boundaries are not sharp and show a gradational transition. This technique provides a novel method for increasing the productivity of senior geoscientists leading to faster and better 3D modeling of ore bodies. In this work, MIK was used in order to determine the ore-waste and also the poor-rich contacts in Sechahun iron deposit in central Iran. Albeit the great advances of complex mining softwares doing the visualization and modeling of complex geological domains, some structures such as dykes in the middle part of deposit cannot be modeled and discriminated from the ore zones, which would lead to an overestimated tonnage. In such conditions, MIK can better delineate the waste blocks within the ore zones, and as the result, it considers the dilution. It significantly decreases the risk of assessments.

3) There is a normal fault in the eastern part of the deposit confined the ore body, which is buried by overburden alluvium sediments and has been ignored during the traditional geological modeling steps, while the MIK modeling delimited the extension of the ore body to the fault position.

4) Comparison of the resultant probability maps with the real contacts on the extracted levels shows that the first indicator model can separate the ore body (poor plus rich) from the waste zone by probability of more than 0.35 with the total reserve of 53 million tons, while the deposit has been previously estimated 64 million tons using ordinary kriging without considering the problems gathering with dilution of the blocks in which dykes are interfered.

5) The second indicator model is applied to separate the rich and poor domains and results show that the blocks with the estimated probability of equal to or more than 0.4 are laid within the rich ore zone consisting of 15.8 million tons reserve, which had estimated previously almost 16.6 million tons using ordinary kriging. This approach assists to reduce the estimation uncertainty especially in the deposits with complex geological context and enhances the accuracy of assessments.

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References


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