Mineral Resources Estimation Based on Block Modeling

by Waterman Sulistyana Bargawa

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Abstract. The estimation in this paper uses three kinds of block models of nearest neighbor polygon, inverse distance squared and ordinary kriging. The techniques are weighting scheme which is based on the principle that block content is a linear combination of the grade data or the sample around the block being estimated. The case study in Pongkor area, here is gold-silver resource modeling that allegedly shaped of quartz vein as a hydrothermal process of epithermal type. Resources modeling includes of data entry, statistical and variography analysis of topography and geological model, the block model construction, estimation parameter, presentation model and tabulation of mineral resources. Skewed distribution, here isolated by robust semivariogram. The mineral resources classification generated in this model based on an analysis of the kriging standard deviation and number of samples which are used in the estimation of each block. Research results are used to evaluate the performance of OK and IDS estimator. Based on the visual and statistical analysis, concluded that the model of OK gives the estimation closer to the data used for modeling.

INTRODUCTION

Many grade estimation techniques are used to determine the potency of mineral resources or reserves. Conventional estimation techniques such as triangular, statistics or cross-section method has been widely abandoned because it is done by hand, so it is not practical and the grade estimation results are often unsatisfactory. Estimation techniques with block modeling was developed using computer tools [1]. Estimation methods using the block model, among others are the NNP (nearest neighbor polygon), IDW (inverse distance weighting) and kriging. OK with IDS estimation technique here used as a comparison. Block modeling is expected to provide an overview of mineralization geometry, grade distribution and the amount of resources.

The study location lies in the area of Pongkor and Cikotok mount, West Java Province of Indonesia (FIGURE 1). Intrusive andesite lithology is exposed in the northern as a part of the study area, and broke to the volcano lithology. Andesite rocks are estimated as a carrier in the form of vein mineralization. The ore veins have average width of 2.5 meters, direction of veins strike around of N12^{0}E and average slope around 75^{0} to the west [2]. FIGURE 2 shows the geological map of Cikidang area West Java Province Indonesia.

METHOD AND MATERIALS

Prediction value in this study is using block kriging [1]. This technique works with parameter fitting of results empirical semivariogram to the theoretical semivariogram as main-base. Initial construction began with the selection of robust semivariogram [3].

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$$\gamma(h) = \left(\frac{1}{2|N(h)|} \Sigma_{N(h)} \left(z(s_i) - z(s_j) \right)^{1/2} \right)^4 \Big/ \left(0.457 + \frac{0.494}{|N(h)|} \right) \tag{1}$$

where $\mathbf{h} = \mathbf{s}_i - \mathbf{s}_j$.

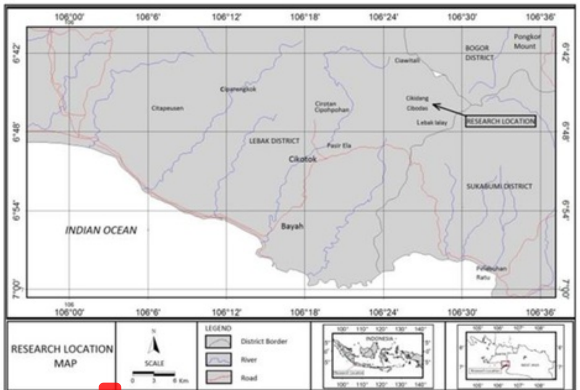

FIGURE 1. Location map of research area

Empirical semivariogram is a manifestation of discrete function which needs to be paired continuously [4]. Semivariogram fitting, here using spherical function formulated as [5],

$$\gamma(h) = \begin{cases} 0, & h=0 \\ C_0 + c\left[1.5\left(\frac{|h|}{a}\right) - 0.5\left(\frac{|h|}{a}\right)^3\right] & 0 < |h| \geq a \\ c_0 & |h| \geq a \end{cases} \tag{2}$$

While weighted least squares (WLS) model formulated as,

$$R(\theta)_{WLS} = MINIMUM \frac{1}{2} \sum_{i=1}^{n} N(h_i) \left[\frac{\hat{\gamma}_z(h_i)}{\hat{\gamma}_z(h_i;\theta)} - 1 \right]^2$$

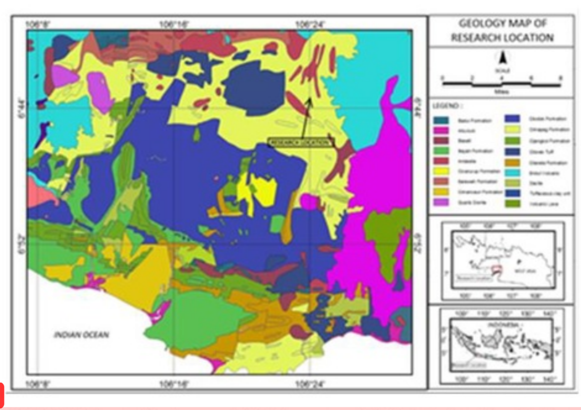

FIGURE 2. Geological map of Cikidang area West Java Province Indonesia

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The principle of grade estimation on ore deposit is to interpolate or extrapolate the sample of it is mineral deposit. Each sample has an influence (or weight) determined statistically. Grade estimation is done at an un-sampled grades location using samples around the site. Generally, the weighting of grade estimation known as the principle of weighted average. In the mining industry, the weighted average principle widely used to calculate the average (or mean) of the variables that exist in mineral deposits [6].

Kriging technique allows a probabilistic interpretation of the mineral deposits or reserve data. In addition, kriging allows for the statistical interpretation of the bias and variance estimation. Simply, kriging produces a set of weights that minimize the variance of the estimation in accordance with the sample configuration around the block and the nature of the mineralization [1 and 5]. Mineralization properties stated in the variogram function quantifies the correlation between the sample chambers. This method is quite accurate because it can take into account of the anisotropy behavior. Two main results obtained from these techniques are estimation and variance or standard deviation of kriging as a measure of reliability [7].

The spatial sample in kriging technique is the data represent the population of other around data (including the un-sampled data). Say, $s_0$is a un-sampled point which will be predicted, then the block prediction, $\hat{Z}_B$ to the value of $Z(s_0)$ can be formulated as[5, 8],

$$\hat{Z}_B = \sum_{i=1}^{n} \lambda_i z(s_i) \tag{3}$$

λ_i is the weight of i-th to the s_0. Un-biasness happen if$\sum_{i=1}^{n} \lambda = 1$, while the optimal condition occurs if the difference of the real sample variance to the estimated sample is a minimum, or $Var(\hat{Z}_B - Z_B) = 0$. Mathematically, written as

$$Var(\hat{Z}_B - Z_B)^2 = E(\hat{Z}_B - Z_B)^2 - \left(E(\hat{Z}_B - Z_B)\right)^2$$

$$= E(\hat{Z}_B{}^2 - 2\hat{Z}_B Z_B + Z_B{}^2) - \left(E(\hat{Z}_B - Z_B)\right)^2$$

$$0 = E(\hat{Z}_B{}^2) - 2E(\hat{Z}_B Z_B) + E(Z_B{}^2) - \left(E(\hat{Z}_B - Z_B)\right)^2$$

Then,

$$E\left(\sum_{i-1}^{n} \lambda_i z(s_i) - Z_B\right)^2 = E\left(\sum_{i-1}^{n} \lambda_i z(s_i)\right)^2 - 2E\left(\sum_{i-1}^{n} \lambda_i z(s_i) Z_B\right) + E(Z_B)^2$$

Variance of block prediction is written as

$$\sigma_B^2 = 2\sum_{i-1}^{n} \lambda_i \bar{\gamma}(z(s_0), B)\bar{\gamma}(B, B) - \sum_{i=1}^{n}\sum_{i=1}^{n} \lambda_i \lambda_j \gamma(z(s_i - s_j) \tag{4}$$

The basic principle of an inverse distance squared (IDS) method is determining of the sample weight (w_i), as a function of distance to the block being sample estimated. An inverse distance method is a linear combination or weighted average value of the grade composite around the block which is defined as follows (valid for n> 0) [1, 2]:

$$Z^*(s_0) = \sum_{i-1}^{n} w_i (z(s_1),\ i = 1,\ldots,n. \tag{5}$$

where: $Z^*(s_0)$=estimation grade for IDS, w_i=sample weight, $z(s_i)$=grade sample

DISCUSSION

Assay data for modeling were obtained from 57 holes of core drilling, ten data obtained from the stope sampling, and three data from the surface. Descriptive statistical analysis performed regardless of the position of each data. The result of this statistic is used as the initial information to interpret the characteristics of the entire sample in general. Based on the statistical analysis conducted on 751 gold assay data and as many as 637 silver assay data, the average values obtained gold assay was 8.81 g/t, with a variance of 193 $(g/t)^2$. The mean of silver assay is 56.4 (g/t), and variance of 6910 $(g/t)^2$. In this case the constructing of a composite data based to homogenize the data interval, so the estimation of each block will be assessed by the sample which is same volume of geometric support. Compositing data interval of 2.5 m selected because of the smallest standard deviation value compared to other composites. Type of rock used in the estimation divided into two parts, namely non-ore veins and ore veins. The data used to estimate, simply the assay or composite data that is in the ore veins.

Gold and silver assay variography done by the searching direction along the average of strike and direction of slope of the ore veins. Fitting theoretical variogram based on a spherical model, as Eq. 2. The calculation based on Eq. 1producesthe parameters as seen in TABLE 1 and TABLE 2.

TABLE 1. Gold and silver assay variogram parameters

Parameter	Gold	Silver
Along strike veins of variogram parameter		
Class interval	5 m	10 m
Nugget	100 $(g/t)^2$	1,800 $(g/t)^2$
Sill	200 $(g/t)^2$	6,910 $(g/t)^2$
Range	30 m	33 m
Down dip veins variogram parameter		
Class interval	5 m	10 m
Nugget	55 $(g/t)^2$	2,000 $(g/t)^2$
Sill	200 $(g/t)^2$	6,910 $(g/t)^2$
Range	30 m	28 m

TABLE 2.Sample search parameter

Parameter	Gold	Silver
▪ Angle from *x* (phi)	77.70^0	77.70^0
▪ Angle from *y* (psi)	–75.00^0	–75.00^0
▪ Anisotropy factor horizontal (afh)	5.00	3.50
▪ Anisotropy factor vertical (afv)	1.25	0.89
Maximum of radius searching		
▪ along strike of ore veins	50.00 m	35.00 m
▪ down dip of ore veins	40.00 m	40.00 m
▪ perpendicular of ore veins	10.00 m	10.00 m

Three-dimensional model of gold-silver ore deposits can be made on the basis of topographic data, geological information, and the levels of investigation results of exploration samples. Topographic modeling is done by digitizing topographic maps. The geological model of mineralized veins is based on the interpretation of 20 cross-sectional shapes of the veins around the west-east orientation. Shape modeling interpretation of vein is conducted by digitization geologist. Geological boundaries are necessary so that the samples are located in the veins not extrapolated to the outside of vein blocks. Grade estimation of OK and IDS performed by database of gold-silver composite. Grade estimation was performed using a minimum composite of 1 and a maximum of 10. The grade estimation of block is only performed on the block which is in the ore veins.

RESULTS AND DISCUSSION

The estimation of resources in block model begins by entering a grade estimation results into the block model. Tonnage block estimation is using variables of the model which is a block density function, block volume, block percentage in the vein and the percentage of topography. Tabulation of gold-silver resources in this model is done at various grades boundary. The gold-silver resource number of block modeling results using OK, IDS, and the NNP (Eq. 3 and Eq. 5) can be seen in TABLE 3 and 4 below. The depiction of a vertical cross-section of each model was used to determine the block model selection. Grade distribution in cross section block is then compared with same cross-section of the composite data (TABLE 5 and 6).

TABLE 3.Number of gold-silver resource based on NNP

COG (g/t)	Tonnage	Gold (g/t)	Silver (g/t)
0	1,030,275	10.38	31.78
4	663,200	15.35	43.44
6	561,810	17.14	49.23
10	445,184	19.48	54.98

TABLE 4.Comparison of the OK and IDS modeling results

Model	Cog	Minimum number of composite=2			Minimum number of composite=3		
		Tonnage	Au (g/t)	Ag (g/t)	Tonnage	Au (g/t)	Ag (g/t)
OK	0 g/t	699,197	10.18	40.96	506,827	11.26	48.02
	4 g/t	475,037	14.33	54.58	369,177	14.86	60.72
	6 g/t	385,273	16.42	64.89	304,287	16.84	72.47
	10 g/t	295,111	18.98	74.96	221,861	20.10	88.52
IDS	0 g/t	699,197	10.31	42.78	496,907	11.57	56.25
	4 g/t	459,987	14.94	59.01	357,327	15.51	72.76
	6 g/t	379,147	16.96	68.97	298,167	17.47	85.39
	10 g/t	309,281	18.99	77.36	235,281	20.01	97.86

The classification of gold-silver resource based on the level of confidence against the block grade estimation. Parameters are used to provide information about the level of confidence is kriging variance distribution. The results of gold-silver estimation resource (TABLE 3 and 4) showed that the decrease in the cut-off grade can improve tonnage resources. Declining of cut-off grade caused more of blocks classified as a resource and the mean grade of the whole block will fall. TABLE 4 shows, the more number of composite samples which is used in the estimation lead to the fewer number of blocks used in the resource/reserve estimation.

TABLE 5 and 6 show that, the results of the estimation on OK and IDS does not show high variations of the composite data, but overall, the OK model is more likely to have a resemblance to the composite grade. Kriging variance (as in Eq. 4) is a function of the sample configuration around the estimated block. In this study, a combination of kriging standard deviation and number of block estimation samples is a criterion that is used to classify the gold-silver resource (TABLE 7 see Appendix). In TABLE 8 (see Appendix) it can be seen that the OK model appears more conservative than the IDS models. OK model over limit to extrapolate the high grades. TABLE 9 (see Appendix) shows that the level of OK block model has a statistical value which is closer to the statistical value of the composite.

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TABLE 5. Statistical comparisons between the gold grade of OK and IDS model at various elevations

Elevation	Statistic	OK (g/t)	IDS (g/t)	Composite (g/t)
1125 - 1100	Mean	5.25	5.50	5.05
	Standard deviation	3.23	3.93	7.87
	Minimum	0.54	0.51	0.24
	Maximum	12.18	14.83	44.68
1150 -1125	Mean	5.35	4.13	6.18
	Standard deviation	3.83	4.06	8.56
	Minimum	0.52	0.51	0.15
	Maximum	27.35	40.34	44.68
1175-1150	Mean	9.17	8.09	10.40
	Standard deviation	5.45	5.67	15.58
	Minimum	0.18	0.15	0.146
	Maximum	19.75	25.2	77.69
1200-1175	Mean	12.27	12.81	14.80
	Standard deviation	13.45	14.44	15.94
	Minimum	0.25	0.18	0.15
	Maximum	52.37	51.84	77.69
1225-1200	Mean	16.45	16.95	15.64
	Standard deviation	12.81	13.43	16.23
	Minimum	0.22	0.21	0.15
	Maximum	64.91	66.14	89.55
1250-1225	Mean	16.05	16.96	15.47
	Standard deviation	11.11	11.44	15.64
	Minimum	1.35	1.19	0.18
	Maximum	57.60	64.87	89.55
1275-1250	Mean	14.21	11.85	15.16
	Standard deviation	7.94	6.03	14.83
	Minimum	5.34	5.39	0.18
	Maximum	36.47	43.04	89.55

TABLE 6. Statistical comparisons between the silver grade of OK and IDS model at various elevations

Elevation	Statistic	OK model (g/t)	IDS model (g/t)	Composite (g/t)
1125 - 1100	Mean	13.77	12.63	19.65
	Standard deviation	3.60	3.23	23.73
	Minimum	6.77	6.8	3.5
	Maximum	38.27	29.97	107.99
1150 -1125	Mean	15.37	14.38	18.98
	Standard deviation	7.40	7.50	21.85
	Minimum	6.77	6.80	3.21
	Maximum	36.84	36.84	107.99
1175-1150	Mean	20.70	20.54	59.53
	Standard deviation	11.77	12.79	11.99
	Minimum	3.55	2.14	3.21
	Maximum	43.51	42.88	663.55
1200-1175	Mean	72.66	80.60	90.62
	Standard deviation	80.41	94.18	173.44
	Minimum	3.73	3.75	3.2
	Maximum	353.66	355.11	663.55
1225-1200	Mean	94.54	102.27	93.53
	Standard deviation	65.94	76.94	93.65
	Minimum	3.96	3.96	3.21
	Maximum	339.59	327.63	663.55
1250-1225	Mean	96.83	96.13	90.41
	Standard deviation	55.59	57.44	90.39
	Minimum	16.22	16.22	3.96
	Maximum	247.46	258.50	663.55

TABLE 7. Classification of gold-silver resource in OK model

Cog (g/t Au)	Measured and indicated			Inferred		
	Ore tonnage	Grade of Au g/t	Grade of Ag g/t	Ore tonnage	Grade of Au g/t	Grade of Ag g/t
0	699,197	10.18	42.78	331,078	10.81	8.55
4	475,037	14.33	36.61	188,163	17.91	10.19
6	385,237	16.42	67.24	176,576	18.93	9.94
10	295,111	18.98	77.09	150,073	20.46	11.49

TABLE 8. Ore tonnage comparison of gold content on OK and IDS*) and difference (%) to OK model

Cog (g/t)	OK Model	IDS Model	difference to OK
0	506,827	496,907	0
4	369,177	357,327	-2.49
6	304,287	298,167	-2.49
10	221,861	235,281	6.05
Cog (g/t)	**Grade (g/t)**	**Grade (g/t)**	**difference to OK**
0	11.26	11.57	1.20
4	14.86	15.51	3.80
6	16.84	17.47	3.74
10	20.10	20.01	-0.04
Cog (g/t)	**Au metal content**)**	**Au metal content**)**	**difference to OK**
0	5.707	5.778	1.24
4	5.486	5.555	1.26
6	5.124	5.209	1.66
10	4.459	4.708	5.58

*) Minimum number of composite for estimating: 3

TABLE 9.Common statistical result on OK and IDS models

Gold	Minimum numberof composite=2		Minimum numberof composite=3		Composite
	OK model	IDS model	OK model	IDS model	
Number of data	4241	4241	3035	3035	389
Mean (g/t)	10.67	10.14	11.45	11.32	12.60
Standard deviation (g/t)	10.00	10.41	10.64	11.11	14.87
Minimum (g/t)	0.15	0.15	0.18	0.15	0.02
Maximum (g/t)	64.91	66.14	64.14	66.14	89.55
Silver	**Minimum number of composite=2**		**Minimum number of composite=3**		**Composite**
	OK model	**IDS model**	**OK model**	**IDS model**	
Number of data	2622	2622	1525	1525	363
Mean (g/t)	56.57	55.64	63.30	62.46	74.03
Standard deviation (g/t)	58.79	64.83	60.96	67.06	86.38
Minimum (g/t)	3.57	0.69	3.55	2.14	1.26
Maximum (g/t)	337.73	341.41	353.66	355.11	663.54

CONCLUSION

Based on the above discussion it can be concluded that OK model is more feasible applied to the modeling of gold-silver resource. Based on kriging standard deviation distribution can be obtained classification of mineral resources. The classification of resources of gold and silver in this study may categorize the amount of resources in the classification of inferred, indicated and measured for gold and silver ore.

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