OPTIMIZATION OF SPATIAL DATA SAMPLE FOR GOLD MINERAL PREDICTION

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ABSTRACT

This study examines the relationship between the results of semivariogram fitting conformity with estimating based on errors produced. The experimental semivariogram estimation was calculated using robust methods, while the theoretical semivariogram function used are spherical and exponential models, with weighted least squares and ordinary least squares approaches. Consistently, the four semivariogram fittings produce root mean square error (RMSE) fluctuates, while the values are proportionally to the median absolute deviation (MAD) generated by ordinary kriging.

Keywords: robust semivariogram, WLS and OLS, ordinary kriging

1. INTRODUCTION

Minerals of mining industry, especially gold mineral, is a business that almost could carries a high risk potentially. The exploration is a part of crucial stage done before starting the exploitation of minerals activity. Failure in exploration, particularly in the amount of reserve prediction, of course, affect the bankruptcy for the company. Therefore, the accuracy and precision in this activity should be desired. The accuracy in gold mineral calculation starts from sampling study. While precision in methods using and calculations become one of the main base.

This study presents three case are, the semivariogram estimated, kriging prediction and optimization of sample used for reserves calculation. Estimation is a tool to get parameters as a base of kriging prediction. These parameters can be obtained from fitting experimental semivariogram with theoretical semivariogram function which in this study, using robust methods. The precision of semivariogram fitting measured by the root mean square error (RMSE) produced, while accuracy for the prediction kriging measured by the median absolute deviation (MAD). The information about optimal data sample used can be seen from the several experiments kriging predictions, i.e. kriging prediction based on errors of original and reduction data. Data reduction is based on 10, 20, 30 and 40 percent losing of original data. In this case, the points of data left used as a predictor for the whole of eliminated data. The changes of deviation value structure that measured by MAD is used to estimate the changes in the behaviour of data.

2. MATERIAL AND METHOD

This study is about kriging prediction of gold resource distributed in the veins. The vein as a sheet-shaped space in the ground where minerals can precipitate. Gold mineral distribution is highly depend on the vein characteristic (Kerrod, 1984). Several major vein characteristics that can be used as reference. Some of the basic characteristics are, mineral or metal components therein are not uniformly distributed in the ore body. Some veins have a dimension that is not too wide, and it's vulnerable to the occurrence of dilution for primary mineral. One thing that also needs to be considered is the possibility of highly gold grade differences and unpredictable, between one host to another, even though it is in a system of veins (Barnes, 1988, Annels, 1991).

Base on this study, geostatistics is a method works based on grade-sample. A number of 128-core drilling samples was obtained from the drilling points in Ciurug veins, area situated in the mountains-Pongkor, Indonesia. Concession of a gold mining company PT. Aneka Tambang UBPE Pongkor located in the area which an altitude of ± 850 m above sea level. With the aim to reduce the environmental damage, underground mining is used in this mining operations.

While semivariogram as a part of geostatistics tool is a mathematical function which is used to recognize the behaviour of gold mineral distribution. Because of data limited, this function as generally then presented as discrete functions. To determine the pattern of continuous validity approaches, fitting to the theoretical functions would be executed. The experimental semivariogram used here, based on robust model (Cressie and Hawkins, 1980). The weighted least squares (WLS) and ordinary least squares (OLS) used as an approach to the fitting of semivariogram function. Two semivariogram function theory of spherical and exponential formula used. The parameters of fitting primarily, sill, nugget and range which is then used as the basis for calculations in kriging prediction.

The robust experimental semivariogram was calculated using the following equation (Cressie, 1993):

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$$\bar{\gamma}(\mathbf{h}) = \left(\frac{1}{2|N(\mathbf{h})|} \sum_{i=1}^{N(\mathbf{h})} \left[\mathrm{Z}(\mathbf{s}_i) - \mathrm{Z}(\mathbf{s}_j) \right]^{\frac{1}{2}} \right)^4 \Bigg/ \left(0.457 + \frac{0.494}{|N(\mathbf{h})|} \right)$$

OLS and WLS model approaches is used, while the spherical and exponential model of semivariogram can be expressed by the following equation in Table-1 and Table-2 (Cressie and Hawkins, 1980, Moustafa, 2000):

Table-1. Least squares models for semivariogram fitting.

	Approach
OLS	$\text{minimum} \sum_{j=1}^{J} \left[\hat{\gamma}(\mathbf{h}_j) - \gamma(\mathbf{h}_j; \theta) \right]^2$
WLS	$\text{minimum} \sum_{j=1}^{J} \left(\frac{\hat{\gamma}(\mathbf{h}_j)}{\gamma(\mathbf{h}_j; \theta)} - 1 \right)^2 N(\mathbf{h}_j)$

Table-2. Semivariogram theory of model based.

	Semivariogram theoretical, $\gamma(\mathbf{h})$	
Spherical	$\begin{cases} 0, \\ C_0 + C_1 \left[\frac{3}{2}\left(\frac{\lvert\mathbf{h}\rvert}{a}\right) - \frac{1}{2}\left(\frac{\lvert\mathbf{h}\rvert}{a}\right)^3 \right], \\ C_0 + C_1, \end{cases}$	**h**=0 0<**h**≤ a |**h**|>0
Exponential	$\begin{cases} 0, \\ C_0 + C \left[1 - \exp\left(-\frac{\lvert\mathbf{h}\rvert}{a} \right) \right], \end{cases}$	**h**=0 **h**≠0

Some kriging methods are used in various studies, but ordinary kriging (OK) is a technique used in this study. OK is a linear extrapolation technique introduced by Matheron (1963). The technique which is assumed based on the stationary principle is believed quite well, because in addition it's consider to the weighted values between points, and also produced the variance prediction which is quite reliable.

Generally, OK prediction system (Van Groenigen, 2000, Giraldo, 2011) which referring to Matheron's equation, as the optimization of objective function value, $\hat{\mathrm{Z}}(\mathbf{s}_0)$ with n observations. It is expressed as:

$$\hat{\mathrm{Z}}(\mathbf{s}_0) = \sum_{i=1}^{n} w_i \, \mathrm{Z}(\mathbf{s}_i).$$

where w_i is the weight of i observation. Kriging variance can be written as:

$$\sigma_{OK}^2(\mathbf{s}_0) = E\left[\mathrm{Z}(\mathbf{s}_0) - \hat{\mathrm{Z}}(\mathbf{s}_0) \right]^2.$$

3. RESULT AND DISCUSSIONS

Before estimating the semivariogram and kriging prediction, the structural analysis needs to be calculated. Structural analysis may use of coefficient of variation (CV) or skewness. Fytas *et al.* (1990) and Journel (1983)reported that semivariogram can works well and produces of a good linear kriging prediction if the coefficient of variation of data is less than one (CV <1). While Dominy *et al.* (1997) and Roy *et al.*(2004) provides more lenient restrictions, namely that ordinary kriging could work well if CV is less than 1.5. As for skewness equal to 0.5 or less, its advised enough using the polygon or inverse distance weighted method. But if the skewness is more than 0.6, preferably is using of kriging method. In this study, statistical values of the coefficient of variation is 0.629. The skewness value here is, 0.882. Therefore, the next process is semivariogram estimations.

Table-3 presents the result of experimental semivariogram estimation refer to the robust method. Distance here means as a distance of each points semivariogram estimation, and *np* is the amount of pairs points. Terms of semivariogram calculation is that, the number of pairs point data should be in excess of 30 (Journel and Huijbregts, 1978). In this calculation as shown in Table-3, the minimum number of pairs point data is, 68. Semivariogram fitting for the four models are as in Figure-1. Model-1 and Model-2 are the fitting models which are based on spherical functions, each based on the WLS and OLS models. As for the Model-3 and Model-4 are the fitting based on exponential functions which also based on WLS and OLS models.

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Table-3. Robust experimental semivariogram estimation.

Distance, h	***np***	$\bar{\gamma}$(h)
17.298	68	2.529
51.894	289	7.085
86.490	385	8.203
121.086	417	10.012
155.683	451	10.227
190.279	491	10.970
224.876	437	10.722
259.472	417	12.233
294.068	358	12.264
328.664	375	9.654
363.260	347	10.037
397.857	343	12.581
432.453	318	11.147

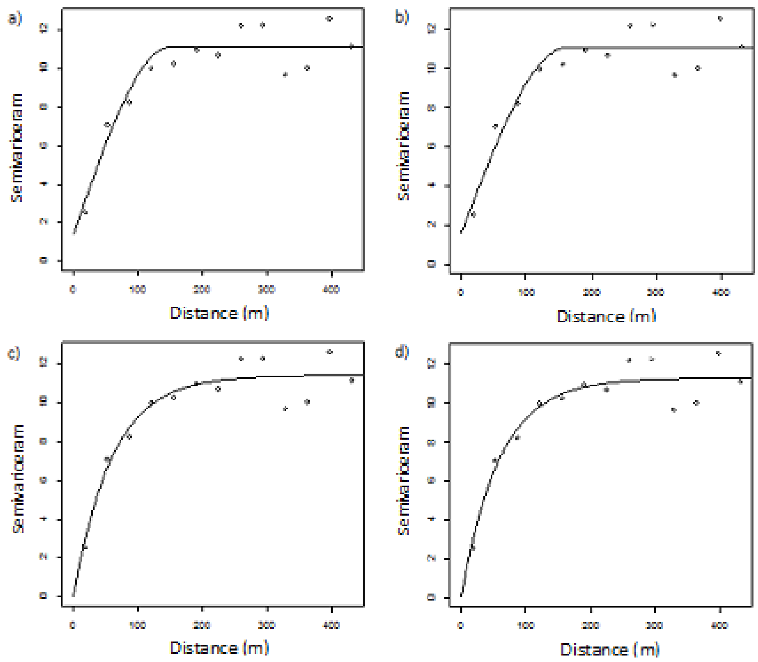

Figure-1. Graff of semivariogram fitting: (a) Model-1, (b) Model-2, (c) Model-3 dan(d) Model-4.

In this calculation, the kriging prediction based on 150×41 grid points, where the distance of each points data is 10. The grid determination is based on the outermost points position. Table-4 presents the RMSE semivariogram fitting exposure. Column 3 is the median absolute deviation (MAD) values for point kriging prediction based on original data. While columns 4 to 7 are the MAD values for data losing (in percent of original data). It appears that consistency ranking between RMSE and MAD happens to the kriging prediction of original data. While in data losing, consistency only happen in Model 3 and Model-4. This applies to the consistency of the data losing 10 percent only.

Table-4. Errors of fitting semivariogram (in RMSE) and point kriging (in MAD) based on data and losing.

Model	Semi-variogram RMSE	MAD of point kriging based on				
		Original data	Losing data (%)			
			10	20	30	40
Model-1	0.830	1.638	1.397	1.397	2.625	2.341
Model-2	0.865	1.683	1.434	1.378	2.638	2.163
Model-3	0.702	1.549	1.410	1.308	2.203	2.891
Model-4	0.683	1.539	1.409	1.299	2.195	2.867

4. CONCLUSIONS

Given the results from this study, the following remarks may be concluded:

- RMSE value based on semivariogram fitting parameters of exponential model (Model 3 and Model 4), are generally smaller than the spherical model calculations.
- The changes between RMSE fitting semivariogram value and MAD prediction kriging point applies consistently only to the prediction based on original data.
- The consistency of the RMSE and MAD values in data losing occur only in the point kriging prediction of 10 percent data losing.

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REFERENCES

R. Kerrod. 1984. Gambaran sains Logam. Translate by: Tony Osman. Malaysia: Federal Publications Sdn Bhd.

J.W. Barnes. 1988. Ore and minerals: Introducing economic geology. Milton Keynes, Philadelphia: Open University Press.

A.E. Annels. 1991. Mineral deposit evaluation: A practical approach. London. New York. Tokyo. Melbourne. Madras: Chapman and Hall.

N. Cressie and D.M. Hawkins. 1980. Robust estimation of the variogram. International Journal of Association for Mathematical Geology. 12(2): 115-125.

N. Cressie. 1993. Statistics for spatial data. New York. Chichester. Toronto. Brisbane. Singapore: John Wiley and Sons, Inc.

M.M Moustafa. 2000. A geostatistical approach to optimize the determination of saturated hydraulic conductivity for large-scale subsurface drainage design in Egypt. Journal of Agricultural Water Management. 42: 291-312.

G. Matheron. 1963. Principles of geostatistics. Journal of Economic Geology. 58: 1246-1266.

J.W. Van Groenigen. 2000. The influence of variogram parameters on optimal sampling schemes for mapping by kriging. Journal of Geoderma. 97(3-4): 223-236.

R. Giraldo, P. Delicado and J. Mateu. 2011. Ordinary kriging for function-valued spatial data. Journal of Environmental and Ecological Statistics. 18(3): 411-426.

K. Fytas, N. Chaouai and M. Lavigne. 1990. Gold deposits estimation using indicator kriging. CIM Bulletin. 934: 77-83.

A.G. Journel. 1983. Non parametric estimation of spatial distribution. International Journal of Mathematical Geology. 15: 445-468.

S.C. Dominy, A.E. Annels, G.S. Camm, P. Wheeler and S.P Barr. 1997. Geology in the resource and reserve estimation of narrow vein deposits. Journal Exploration and Mining Geology. 6: 317-333.

D. Roy, S.D. Butt, and P.K. Frempong. 2004. Geostatistical resource estimation for the Poura narrow-vein gold deposit. CIM Bulletin. 97(1077): 47-51.

A.G. Journel and C.J. Huijbregts. 1978. Mining geostatistics. New York: Academic Press.