Copper resource estimation in PT X Batu Hijau, Regency of West Sumbawa, West Nusa Tenggara Province using geostatistical method

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Abstract. The presence of copper deposits below the earth surface is generally disordered and its spread is uncontinuous, has varying grades, so it has a high degree of uncertainty in the estimation. One method of estimation uses geostatistics (kriging) where this method is suitable for mineral deposits that are full of uncertainties. The method is strongly influenced by geological data, models and information points (drill hole data). Kriging will estimate the uninformed area by connecting the information points around it. The research was conducted at PT "X", located in Batu Hijau, West Sumbawa regency, West Nusa Tenggara Province, with the lithology of the forming of tonalite intermediates. The data used is a composite data from a combined fifteen-meter hole assay with the number of 1123 sample points. Spatial variations of copper content are known from the results of data processing. Estimated results with the kriging method found that the level of each block varies from 0.2 percent to 1.5 percent with total copper amounts of 3.4 million tons and the value of kriging variance per block varies from 0.05 to 0.16. Relative kriging standard deviation (RKSD) is used for copper resources classification in measured, indicated and inferred categories. The result of RKSD is copper measured resources of ± 700 tons, copper indicated resources ± 400 thousand tons, and copper inferred resources ± 3 million tons.

Keywords: copper deposits, geostatistics, kriging, resources, relative kriging standard deviation

1. Introduction
In the application of geostatistics (kriging) on copper deposits, spatial variations should be known before determining the estimate of resources and resource classification by the relative kriging standard deviation (RKSD) method.

The aim of this research are:
1. Knowing the spatial variation of copper deposit in the Batu Hijau.
2. Knowing the result of estimation of copper resources at Batu Hijau by using kriging method.
2. The Geostatistical Approach

2.1 Basic Statistics

Basic statistics is a scientific method of classifying, summarizing, presenting, interpreting, and analyzing data in order to support valid and useful conclusions that can form a basis of reasonable conclusions. Basic statistical analysis, such as:

1. The average is a value representing the middle of a set of data values
   \[ \bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \]

2. Standard deviation is a measure of the spread of a population.
   \[ \sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \]

3. Variance (variance), is the square of standard deviation.
   \[ \text{variansi} = \sigma_x^2 \]

4. The coefficient of variation is a comparison of the standard deviation of the average count.
   \[ CV = \frac{\sigma_x}{\bar{x}} \]

5. Skewness and Kurtosis

2.2 Variogram

Variogram is a graph that displays the spatial variation of data at a certain distance. The making of variogram requires the search direction of data pair (directional or omnidirectional), the lag of tolerance, the angle of tolerance, and bandwidth.

Figure 1 2D Directional variogram source: Pyrcz, 2014 [10]

Figure 2 3D Directional variogram

After obtaining the data pairs, the value of variation between data at distance is calculated based on the following equation:
If $\gamma (h)$ values are plotted on the variogram an experimental variogram will be generated.

$$\gamma_h = \begin{cases} \sigma_0^2 \left( \frac{3h^3}{2a^3} \right), & \text{untuk } h \leq a \\ \sigma_0^2, & \text{untuk } h > a \end{cases}$$

Source: Oliver, [11]
Figure 3 Experimental example of the directional variogram

After that variogram modeling is done by making a linear line from the following equation:

From the results of the modeling, three main parameters can be seen namely sill ($C$), range ($a$), and nuggets effect ($C_0$).

Source: Emanuele Barca, 2017 [6]
Figure 4 Experimental variogram after modeling

2.3 Cross-Validation

After the experimental variogram is modeled, it is necessary to validate that the created experimental variogram can be used in kriging calculations, where the test is performed using cross-validation method. The result of the estimated value and the actual value at that point is plotted on the graph $x$, $y$ with a linear line with the equation:

$$x = y$$

In kriging estimation, it is known as the best linear unbiased estimator (BLUE) which is best said when the plot points on the graph approach the linear line and are said to be unbiased when the plot points are relatively balanced between those above the linear and below.
2.4 Resource Estimates

The estimation of the resources in the minerals can use various methods, among which there are those using weight as controller from data points around the point to be estimated, where the sum of the weights (Σλ) will be 1 (one).

The general equation of the estimate is set forth in the following equation:

\[ Z(x_0) = \sum_{i=1}^{n} \lambda_i \times Y_i = 1 \]

Kriging is one of the estimators used in mineral estimates in general. The weight of the estimate comes from the distance and spatial variation between the data and between the data itself obtained in the experimental variogram experimental results that have been valid.

2.5 Estimation Software

In the estimation of minerals, two software are used for basic statistical calculations, experimental variogram creation, experimental variogram modeling, cross-validation, and kriging estimation. The software used are Snowden Supervisor and SGeMS.

Snowden Supervisor is a geostatistical software where Supervisor can calculate basic statistics until cross-validation. While in kriging estimation, SGeMS software is used. From the estimation results, each block is calculated as the tonnage of each color (indicating the difference in the value of the calculated content) in Microsoft Excel software with the formula:

\[ \text{Ore tonnage} = \sum \text{area of block} \times \text{block thickness} \times \text{grade} \times \text{ore density} \]

2.6 Resource Classification

In classifying the resources of large epithermal copper deposits and gold deposits according to Blackwell (2002), we can use the relative kriging standard deviation (RKSD). The sequential classification sequences are generally:

1. Identify areas of mineralization
2. Identify mineralized areas above the cut of grade
3. Classify the area above the cut of grade based on a certain value of the RKSD calculation.

The equations used in the classification are set forth in the following formula:

\[ RKSD = \pm 1.96 \left( \frac{\sigma_{SB}}{Z_{SB}} \right) \]

Measured 0.3 ≤ Indicated 0.5 ≤ Inferred
3. Methodology
This research was conducted at PT X Batu Hijau, West Sumbawa Regency, West Nusa Tenggara Province. Research is quantitative by performing calculations in the form of geostatistical estimation of resources.

The working procedure for data processing starts from the data preparation stage to the resource estimate.

1. Preparation of data
   Data is generated by the form of a comma delimited (.csv) and delimited text tabs (.txt) using Microsoft Excel software that can be loaded on both SGeMS and Snowden Supervisor software.

2. Analytical Statistics
   Furthermore, the drilling data are tested analytical statistics in the form of histogram and probability plot graphic.

3. Experimental variogram
   Furthermore, the analytically tested data can be processed into the experimental stage of the variogram. The data search direction for variogram calculations is made in omnidirectional with the angle of tolerance 90 °, lag by 75 meters, and lag of tolerance of 37.5 meters. Further variogram modeled by using the spherical method so that obtained parameters sill (C), nugget effect (C0), and range (a).

4. Cross-Validation
   To be able to use variograms that have been created in the previous stage, variograms need to be tested before to be valid.

5. Resource Estimation
   Once a valid variogram is obtained, it can be estimated using copper resources SGeMS software.

4. Case Study
4.1 Geology of Batu Hijau
Batu Hijau area is an island arc that produces gold-copper porphyry deposits. The Batu Hijau location is in the active tectonic zone of the Sunda-Banda Batu Hijau magmatic arc located at in uplift rock blocks, 30 km away from the left-lateral oblique-slip fault zone, this appropriation controlling the dispersion of Miocene-volcanic sedimentary rocks.

As for Garwin [7], the Batu Hijau area belongs to a magmatic arc and is a Cu-Au deposit in Tonalite that is in the Pliocene.

4.2 Stratigraphy of Batu Hijau
Batu Hijau area consists of four units of rock, with sequences from old to young, such as Volcanic Lithic Breccia, Diorite, Intermediate Tonalite, and Young Tonalite.

Source: Geological Dept. P. NNT, 2016 with modifications
Figure 6 Geological section of the east-west direction
5. Data
The data used in the resource estimation uses exploratory drill hole data and with the number of drill holes totaling 595 holes with varying copper resources in Batu Hijau, only the lithology of intermediate tonalite is applied, but the lower-core domains of the lithology are not included in the calculation and it is assumed that the copper weight is considered to be 2.7 tons per cubic meter.

Table 1 Detailed drill hole lithology of tonalite intermediate rocks

| Data   | Number of Data | Grade | Std Dev | CV   |
|--------|----------------|-------|---------|------|
|        | Average        | Min   | Max     |      |      |
| Assay  | 5.696          | 0.815 | 0.02    | 4.29 | 0.388 |
| Composite | 1.123        | 0.815 | 0.116   | 2.162| 0.311 |

6. Results and Discussion
From the analytical statistical test results, it is known the average value of 1123 data used is as much as 0.815 percent. The coefficient of variation value also showed the value to be less than 0.5 so the data is not so varied. Similarly, the skewness results show the frequency of data that is at low levels almost equals high levels. In addition, the probability plot created shows the existence of extreme data (outlier) as much as 0.2 percent or from the overall data.

![Histogram and probability plot of copper content in intermediate tonalite](image)

Figure 7 Histogram and probability plot of copper content in intermediate tonalite

After the analytical statistic test was done, experimental variogram of existing composite data with lag and angle tolerance of 90° was obtained. The value of nugget effect (C₀) was 0.035, sill (C) of 0.063 and the range (a) was 140 meters.
Cross-validation is done in order to test experimental variograms that have been modeled whether to generate a BLUE estimate.

From the plot result graph, the value of the sample and the estimation rate shows a good correlation where both variables are related to 72 percent. In addition, there is also a linear regression equation where the estimation rate can be known by adding 0.42 percent and half the sample value. For example, if the sample rate value is 1 percent, then the estimated rate is half of 1 percent plus 0.42 percent resulting in an estimated rate of 0.92 percent. However, the actual rate of estimation and sample content is relatively the same ie 0.82 percent.
In the estimation of copper content with SGeMS software, an estimation or grid boundary is specified. However, due to the lack of symmetrical ore body and the limited ability of the software to create a grid corresponding to the shape of the ore body, the grid is divided into five so that the estimated error due to the limitation is not too large. After that, based on the nugget effect, sill, and range data obtained at the experimental stage of variogram variation, an estimate of the levels in each of the three-dimensional blocks was available and the total resources of 3.4 million tonnes of copper were recorded in the lithology of tonalite intermediates. In addition to the estimated copper content, it is also known that the value of kriging variance in each block.

Figure 10 Grid to bolt the kriging block on SGeMS

Figure 11 Estimation results (a) copper content and (b) kriging variance in grid 1

Figure 12 Estimation results (a) copper content and (b) kriging variance in grid 2
From these results visually seen blocks with low variance tend to be in the center of the ore body due to the amount of data that is gathered in it. But most variants are in green to yellow.

Furthermore, the classification of relative kriging standard deviation (RKSD) generated a measured quantity of resources of 700 tons, a designated resource of 400 thousand tons, and inferred resources of 3 million tons of copper. The classification results show the highest number of inferred resources, this is due to one of them because the spatial data point average of more than 50 meters. When looking at SNI 4726 of 2011 on resource classification, at distances above 50 meters, the available resources are categorized inferred resources. In addition, the limitations of SGeMS software that can not limit the estimation area according to its lithologic form are also contributors to estimation errors.

7. Conclusion
Based on the results of research on the application of geostatistics on copper resource estimation in Batu Hijau PT Newmont Nusa Tenggara, it can be concluded:
1. Variogram results show that the oral body (intermediate Tonalite) has no dominant direction of continuity, so the variation is relatively the same in all directions (Omnidirectional) with 0.080, 0.062, 0.073, 0.07, and 140 meters of nugget effect 0.05 with a searching area which is spherical.

2. Total estimation by using kriging method yield copper resource as much as ± 3.4 million ton while RKSD classification result shows measured resource amount about ± 700 ton, designated resource ± 400 thousand ton, and inferred resource ± 3 million ton.

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