PROCEEDING-Classification of nickel laterite resources

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Classification of Laterite Nickel Resources Using the Average Distance Approach

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Abstract

The resource classification system helps protect producers and consumers from ambiguous reporting of mineral resources. Classification systems have been introduced in many countries, but they are often general, so they are not easy to apply in the field. Geostatistical approaches are often inaccurate on data with high nugget values. The system requires sophisticated knowledge and takes time to understand, while field practitioners are eager to immediately get mineral resource classification results. This study aims to introduce the average distance from the borehole as a mineral resource classification parameter. In this study, modeling and grade estimation uses a block model with nearest-neighbor polygon and inverse distance weighing techniques as grade estimation techniques. The highest weight in the NNP estimation technique is the closest sample, while the IDW weight depends on the distance; therefore the NNP and IDW techniques use distance considerations only. Based on the histogram of the average distance, the populations in the graph show the classification as inferred resources, indicated resources, and measured resources. The application of the average distance technique for the classification of laterite nickel resources uses the block model.

Keywords: Classification, Resource, Nickel Laterite, NNP, IDW

INTRODUCTION

Mineral resources are vital for the economic growth of a country and maintain the quality of human life. The availability of mineral resources depends on the material, technical, operational, economic, social, environmental, and regulatory conditions (Andrea et al., 2021). These mineral resources increase the prosperity and security of modern society because mineral resources can ensure sustainable economic development. In many countries, especially developing, mineral resources have long been the focus of international attention (Zhai et al., 2021). A stable, sufficient and sustainable mineral supply is the right policy to protect the government. Research shows that mineral-producing countries such as the United States, China, and the European Union dominate the international trade of 24 mineral strategies from 2009 to 2018 for various minerals (Zhua et al., 2020). The development of mineral trade in the future requires a classification system to protect producers, consumers, and financial institutions. The world must be able to accept this system of mineral resource classification.

The classification system requires the right approach, easy to reach, applicable, and practical in the mining industry. Standard classifications, which include information on different types of resources, are required. Many mineral resource classification systems have been developed. This classification system is widely used in some countries with abundant mineral resources, such as China. Resource classification is important to ensure the country's economic security through the supply of mineral resources (Yu et al., 2021). The Polish classification system is essential as a guideline for implementing the Polish Minerals Policy (Galos et al., 2021). In the UK, resource classification is must-have information

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for information on land use planning processes and the development of mineral supply strategies (Bide et al., 2020). The codes or standards for reporting mineral resources in Indonesia are SNI (2019) and KCMI (2017) (Setyadi & Anggayana, 2013).

LITERATURE REVIEW

Mineral resource reporting system implemented by a competent person as a "qualified person" who has experience with certain minerals (Kenneth, 2017). This "qualified person" needs a tool as a standard for classifying mineral resources. Currently, geostatistical methods have been developed for the classification of mineral resources. Many studies have been developed as methods for the classification of mineral resources, DHSA (borehole spacing analysis) (Heriawana et al., 2020; Zulkarnain & Bargawa, 2018; Bertoli et al., 2013; Sadeghi et al., 2015). The DHSA method for resource classification using global variance estimation techniques has been used in various BHP Billiton Mitsubishi Alliance ('BMA') coal mining and operations projects since 2004.

Application of geostatistical methods for modeling and estimating mineral grades, identifying and evaluating high-grade ore zones from low-grade ore zone. It was not only developed for grade estimation, but also developed for the classification of mineral resources. Therefore, geostatistical methods with the usual kriging approach (OK) are very important for mining engineers and geologists (Bargawa et al, 2021; 2020; Bargawa & Tobing, 2020). Geostatistical modeling determines the spatial variability as the basis for estimation (kriging) of mineral resource grades (Iguzquiza et al., 2013). Research on OK through the kriging variance approach has been used to design soil sampling in agricultural areas (Sun et al., 2019). The application of the variogram is one of the most critical processes in model building (Liu et al., 2019) to increase the confidence of mineral resources (Talebi et al., 2019). All of these geostatistical approaches require sophisticated knowledge and take a lot of time to understand. If the data is relatively heterogeneous, the geostatistical approach is not optimal. This study uses NNP and IDW techniques for modeling and estimating mineral grades and applies the mean distance as an approach to mineral resource classification. A case study was conducted on laterite nickel resources to classify inferred, indicated, and measured mineral resources.

RESEARCH METHOD

The research methodology consists of data entry, statistical analysis, block modeling, resource estimation, and resource classification into inferred, indicated, and measurable. The data used for this modeling is drilling data consisting of assay, collar, survey, and geology. Statistical analysis was performed on the assay and composite data. This analysis aims to ensure that the data used is clean and valid. The resource model was made to limit the estimation of nickel content in a population in the study area so that the estimated nickel grade is not extrapolated beyond the mineralization boundary. Topography is a collection of coordinates from the digitized results that shape the surface of the research area. This topographic model is used to limit the extrapolation of grades in the vertical direction.

The resource model is used as the basis for the construction of a 3-dimensional block model (Samanlangi, 2015). Block size is a function of the mineralization geometry in the study area and the mining system to be used. The block model is obtained from the ore body in the form of a 3-dimensional block. The block model covers the entire ore domain based on previous drill and topographic data. The block size uses the rule (Jara et al., 2006) of a quarter of the average borehole distance of 50 m, which is 12.5 x 12.5 m with a block thickness of 1 m.

Nickel grade estimation in this study used NNP and IDW techniques. The formula for the NNP estimation technique is as follows (Bargawa, 2018):

$$Z^* = \sum_{i=1}^{n} w_i . Z_i \qquad (1)$$

The weight, w_i , of NNP gives the greatest weight at the closest distance to the estimated point or block. Distance parameters and power usage strongly influence the IDW technique. The IDW technical formula is (Blanco et al., 2017):

$$Z^* = \frac{\sum z_i\left(\frac{1}{d_i^k}\right)}{\sum \frac{1}{d_i^k}} \qquad (2)$$

where:

Z^* : IDW estimate
Z_i : grade-i
d_i^k : distance-i
k : power

Grade estimates were applied to each limonite and saprolite zones. Resource estimation is based on the block model framework. The estimated block grade is influenced by the grade of the nearest sample (Hekmat & Osanloo, 2010). The classification of nickel resources in this study uses the average distance value. The estimated average distance value is the value of calculating the average distance between the composite data and the estimated block. Based on this mean distance value, the populations in the histogram indicate three classifications, namely measured, indicated, and inferred resources.

FINDING AND DISCUSSION

Resource estimation is based on resource modeling with topographic and geological boundaries. Resource tonnage is a multiplication between block volume and density (Marek, 2001). The estimation of nickel resources in this study uses the Micromine 2020 application based on the block model construction, a function of the mineralization geometry in the research area, and the mining system used. The minimum, maximum coordinates, topographic model, and final borehole depth are the factors that limit the block model area so that the estimated nickel content is not extrapolated outside the mineralized area.

The number of assays from 68 drill holes is 760 data in the limonite zone and 447 data in the saprolite zone. The CV value in the limonite zone is 0.29, and the limonite zone is 0.39. The size of the block dimensions in this study is (12.5x12.5x1) m based on the block model concept in Hustrulid & Kutcha's study (Hustrulid et al., 2013) where the model block size is not less than a quarter of the average borehole interval of 50 m. In the micromine block model in the form of an empty block (blank model), then these blocks will be filled by the estimated grade resulting from the estimation process. After all the blocks are filled with the estimated grade, the volume and tonnage estimates are obtained based on density (1.75) at the study site.

This resource estimation was carried out in each limonite and saprolite zone with different estimation techniques. The estimation results are compared with exploratory data using cross-validation analysis, cumulative probability curves, and 2D cross-section visualization (not discussed in this paper). Based on the analysis results, the estimation technique is used in the limonite zone using the IDW technique while for the saprolite zone using the NNP technique. The classification of nickel resources in this study uses the average distance value. The estimated average distance value is the value of calculating the average distance between the composite data and the estimated block. Based on this average distance value, nickel resources are classified into three categories: measured, indicated, and inferred (Figure 1).

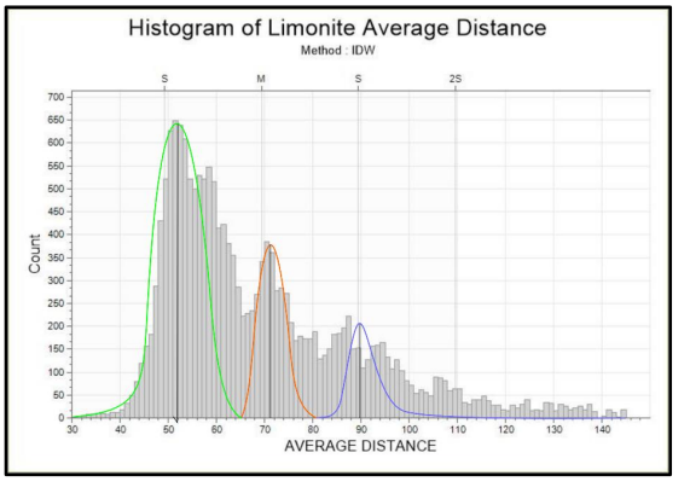

Figure 1 Histogram of average distance in limonite zone using IDW

Based on the histogram above (Figure 1), three data populations are marked by three data peaks. The population data shows the classification of nickel resources, namely measured, indicated, and inferred. The closer the average composite data distance is to the block estimate data, it is classified as a measured resource. The farther the data from the block estimate to composite data is, the estimation results are classified as either indicated or inferred resources.

Based on Figure 1 above, the histogram of the IDW estimation method in the limonite zone at an average distance of 30-65m is a measured resource classification, an average distance of 65-81m is an indicated resource classification, and an average distance of 81-145m is an inferred resource classification. Table 1 below shows the tonnage, grade, and classification of resources based on the average distance estimated using the IDW method in the limonite zone.

Table 1 Nickel resource classification using average distance in the limonite zone (IDW method)

Grade	Resources (wmt)			Total (wmt)	Average grade (%Ni)
	Measured	Indicated	Inferred		
0.0 – 0.5	0	0	0	0	0
0.5 – 1.0	502,000	432,000	296,000	1,230,000	0.92
1.0 – 1.5	2,146,000	626,000	845,000	3,617,000	1.12
1.5 – 2.0	0	0	0	0	0
2.0 – 2.5	0	0	0	0	0
Total	2,648,000	1,058,000	1,141.000	4,847,000	1.02

Based on the histogram average distance analysis above, it results in the classification of nickel resources as follows: measured resources are 2,648,000 tons, indicated resources are 1,058,000 tons, and inferred resources are 1,141,000. The total nickel resource is 4,847,000 tons with an average grade of 1.02% Ni.

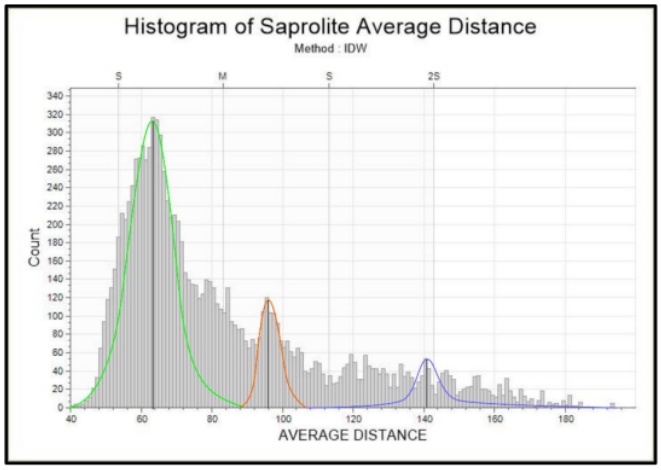

Figure 2
Histogram of the average distance using the NNP method in the saprolite zone

Based on the histogram of the average distance using the NNP estimation method (Figure 2) above, the classification of resources in the saprolite zone at an average distance of 40-91 m is measured resources, an average distance of 91-112 m is indicated resources, and an average distance of 112-200 m is inferred resources.

Table 2 below shows grade-tonnage and resource classification based on average distance using the NNP method in the saprolite zone.

Table 2 Classification of nickel resources based on average distance using the NNP method in the saprolite zone

Grade	Resources (wmt)			Total (wmt)	Average grade (%Ni)
	Measured	Indicated	Inferred		
0.0 – 0.5	37,000	14,000	86,000	137.000	0.40
0.5 – 1.0	22,000	5,000	32,000	59,000	0.70
1.0 – 1.5	370,000	119,000	165,000	654,000	1.34
1.5 – 2.0	1,000,000	157,000	96,000	1,253,000	1.75
2.0 – 2.5	553,000	38,000	173,000	764,000	2.15
2.5 – 3.0	35,000	36,000	1,000	72,000	2.64
Total	2,017,000	405,000	457,000	2,879,000	1.49

Based on the histogram average distance analysis above, the tonnage of nickel resources with measured resource classification is 2,017,000 tons, indicated resources of 405,000 tons, and inferred resources of 457,000. The total nickel resource is 2,879 ,000 tons with an average grade of 1.49% Ni.

Because the cut-off grade provides information about the lowest grade that is still profitable when mined, the relationship between grade and tonnage of laterite nickel is very important to state inventories of laterite nickel resources in decision making at the mine planning stage. Figure 3 and Table

3 below show the relationship between grade and tonnage, the determination of the cut-off grade affects the tonnage of laterite nickel resources.

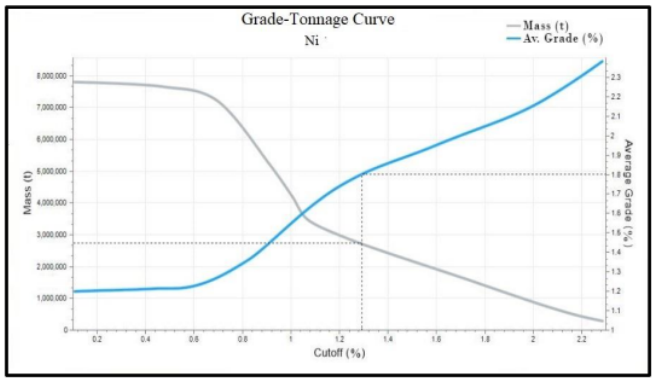

Figure 3 Grade-tonnage curve with an example of an average grade of 1.8% Ni

Table 3 Tabulation of the relationship between tonnage and nickel grade

Cut-off grade (%)	Average Grade (Ni) (%)	Tonnage
0.2	1.21	7,785,586
0.4	1.22	7,699,453
0.6	1.23	7,585,430
0.8	1.35	6,152,891
1	1.55	4,308,555
1.2	1.76	2,916,211
1.4	1.85	2,495,938
1.6	1.98	1,836,133
1.8	2.08	1,385,234
2	2.18	879,648
2.2	2.34	353,008

Figure 3 and Table 3 show a low cut-off grade, resulting in a higher tonnage of nickel resources, while an increase in the cut-off grade will reduce the laterite nickel tonnage. This grade-tonnage curve becomes the basis for economic considerations to obtain optimal benefits in the mineral industry.

CONCLUSION AND FURTHER RESEARCH

The average distance approach using the concept of the closest distance from the sample to the estimated block is an alternative if the geostatistical method does not produce an informative variogram. Modeling and estimating grades of laterite nickel ore using NNP and IDW techniques produces an average distance value that can be used to classify laterite nickel resources. The grouping of populations in the average distance histogram becomes a consideration for classifying inferred, indicated, and measured resources.

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