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Integrating artificial neural networks and geostatistics for optimum 3D geological block modeling in mineral reserve estimation: A case study

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ABSTRACT

In this research, a method called ANNMG is presented to integrate Artificial Neural Networks and Geostatistics for optimum mineral reserve evaluation. The word ANNMG simply means Artificial Neural Network Model integrated with Geostatiscs. In this procedure, the Artificial Neural Network was trained, tested and validated using assay values obtained from exploratory drillholes. Next, the validated model was used to generalize mineral grades at known and unknown sampled locations inside the drilling region respectively. Finally, the reproduced and generalized assay values were combined and fed to geostatistics in order to develop a geological 3D block model. The regression analysis revealed that the predicted sample grades were in close proximity to the actual sample grades. The generalized grades from the ANNMG show that this process could be used to complement exploration activities thereby reducing drilling requirement. It could also be an effective mineral reserve evaluation method that could produce optimum block model for mine design.

1. Introduction

Mineral deposits, due to the geological processes involved in their deposition, are very complex structures to model. Before mine development, the reserve of any deposit must be estimated. The most important factor in reserve estimation is the distribution of the ore grade which is always assumed to be a function of distance.

For the past five decades, the mining industry has adopted and applied geostatistics for mineral reserve estimation. This is because it provides powerful tools for modeling most of the aspects of an ore deposit. The main steps involved in estimation using geostatistics are as follows: (1) obtain the variogram model of the deposit, (2) fit a standard model to the variogram and (3) produce block estimates using any of the available estimation or simulation techniques.

However, this method of estimation only considers the spatial continuity as the main factor. Over the years we have learned that there are other factors like geological structure, deposition environment, type of ore, and degree of mineralization that also need to be considered. To date, the biggest challenges in using geostatistics lie in the failure of variogram modeling, due to the non-stationarity and normality of the data.

Recent developments in computing technologies have produced several machine learning algorithms, especially Artificial Neural Networks (ANNs), which have the ability to operate nonlinearly. They can be used in the estimation of ore grades. With this technique, no assumptions are made about any factor or relationship regarding the spatial variation of ore given the availability of drillhole data. ANNs learn the underlying functional relationship present in the data from the samples that are made available to them.

In this research, as shown in Fig. 1, an ANN model is presented with assay data collected directly from drilling for the purposes of training, testing and validation. Because the drillholes used covered a reasonable part of the deposit, the trained network had sufficient information to characterize the spatial variation of ore grades in the region encompassed by the drillholes.

The trained network was not only able to reproduce the assay data that was trained on, through generalization, it was also able to interpolate the ore grades at locations inside the drilling region. The network's model performance was assessed by two estimation errors, namely, the mean squared error (MSE) and the correlation coefficient (R^2).

In order to construct a 3D model to provide a realistic description of the deposit, the ANN was integrated with geostatiscs. The

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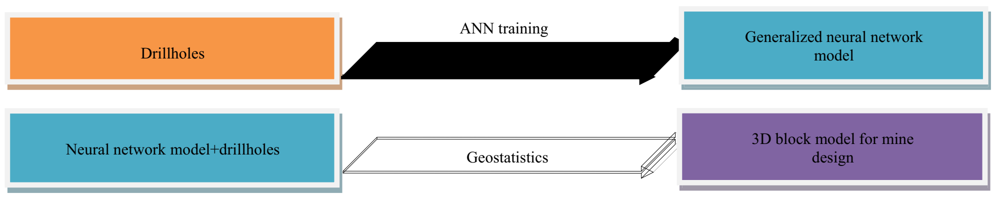

Fig. 1. Diagrammatic drawing of the research.

reproduced and the generalized data were fed into geostatistics to produce the gridded 3D geological block model, ANNMG.

The performance of the ANNMG method was validated by comparing results with ordinary kriging (OK). Obtained results show that the reproduced assay data and the generalized grades could produce optimum block estimates when fed into geostatistics.

Finally, the generalizations, at sampled and unsampled locations, showed that integrating ANNs and geostatistics minimizes drilling requirement for mineral resource evaluation [1–15].

2. General geology and description of the study area

The study area is a mineral sand deposit located on the South Western region of Sierra Leone, roughly at latitude 7°40′N and longitude 12°20′W. Currently, the company developing this mineral lease is exploring this deposit to determine its mining feasibility.

Fig. 2 shows the location map of the deposit encompassing the drilling region and overlain with the drillholes used. The deposit is one of the four largest mineral sand deposits developed in the mining lease area.

The deposition is a result of the rivers' tributaries crisscrossing all over the area, stripping off materials from the adjacent mountains. The mineral distribution pattern comes in two folds and is mostly observed within the interfluves. Geochemical analysis of the deposit show secondary surface enrichment averaging 1.99% heavy minerals, rutile of 0.81% with thickness being 8.9 m.

3. Data analysis and spatial modeling

The assay data used in this study consists of 2880 composite samples from 302 drillholes. The assays included sample coordinates (easting, northing, and elevation), length of sample, and ore grade. Sampling was done at a regular interval. The mineral deposit was estimated using composited drillhole data with a 1.5 m sampling interval.

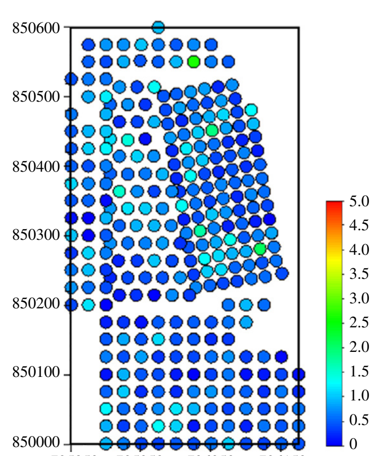

Fig. 2. Location map of the drillholes in the studied area.

Statistical analysis conducted on the composite samples displayed a significantly large grade variation, with a mean and standard deviation of 0.84% and 0.43% respectively. The coefficient of variation was, however, less than one (1). For ANN training purposes, the data was normal score transformed. Table 1 shows the summary statistics. Fig. 3 shows the histogram plot of clustered and normalized data of the ore grades. Visual observation of the histogram plot reveals that the drilling data is composed of a large proportion of low-grade values and a minimal proportion of extremely high-grade values.

After data analysis, the spatial continuity was explored by constructing semivariogram models. In the spatial studies, both directional and omni-directional variograms were constructed. The spatial structures revealed significant contributions from the nugget, thereby indicating difficult variogram modeling conditions.

The directional variogram model provided a better understanding of the deposit and enabled us to search for anisotropies. Fig. 4 shows the directional variogram model fitted with a standard exponential model and Table 2 shows the parameters from which the directional variogram was constructed.

Large proportions of the spatial variability occurring from the nugget effect indicate the presence of a poor spatial correlation structure in the deposit over the study area, and the variogram figure also indicates zonal anisotropy. This anisotropy was taken into account during ordinary kriging.

4. Principles of artificial neural networks for grade estimation using the backpropagation technique

In 1986 David Rumelhart, Geoffrey Hinton, and Ronald Williams wrote a paper describing the use of several ANNs where the backpropagation algorithm works far faster than earlier approaches to learning, making it possible to use neural network applications in many areas. The attraction of neural networks is that they are best suited for solving problems that are the most difficult to solve by traditional computational methods.

Figs. 5 and 6 show the schematic representation and the weighting function of a neuron. The principle of the backpropagation technique is that each neuron receives a signal from the neurons in the previous layer, and each of those signals is multiplied by a separate weight value. The weighted inputs are summed, and, passed through a limiting function called the sigmoid function which scales the output to a fixed range of values. The output of

Table 1
Summary statistics.

Statistics	Values
Mean	0.84
Standard deviation	0.43
Coefficient of variation	0.51
Median	0.79
Minimum	0.00
Maximum	4.12
Upper quantile	1.04
Lower quantile	0.56