Optimization of Open Pit Mine Design by Integrating Geostatistics and Artificial Neural Networks

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論 文 名　：　Optimization of Open Pit Mine Design by Integrating Geostatistics and Artificial Neural Networks　（地質統計学と人工ニューラルネットワークの統合化によるオープンピット鉱山設計の最適化）

区　　分　：甲

論　文　内　容　の　要　旨

The mining industry, over the years, has adopted and applied geostatistics for mineral reserve estimation. The biggest problem in geostatistics is the failure of variogram modelling due to the non-stationarity and normality of drilling data. Factors such as geological structure, deposition environment, type of ore and degree of mineralization need to be considered in addition to the spatial continuity studied in the variogram.

It has been shown that Artificial Neural Networks (ANNs) have the ability to operate nonlinearly and make no assumptions about any factor or relationship regarding the ore's spatial variation obtained from the drillhole data. Therefore, ANNs can be used to learn what underlying functional relationship is present in the data based on core samples in the drillholes.

Previous research on mineral reserve estimation has been carried out using geostatistics and ANNs separately. The research concluded that both approaches to mineral resource evaluation perform equally, and in some cases, one outperforms the other. Since geostatistics has been the most predominantly accurate predictive tool for the mineral grade of a deposit, and ANNs have been used to learn about the underlying functional relationship present in the data, this research proposes combining these two methods for optimum mineral reserve estimation.

This research presents the method integrating artificial neural networks and geostatistics, naming it Artificial Neural Networks Model with Geostatistics (ANNMG). The objective is to apply ANNMG to reduce the number of required drillings by using the model to generalize drillhole grades at un-sampled and sampled locations inside the mine area.

In the research, the ANNMG model was trained, tested and validated using assay values obtained from 3D-drillhole samples. The validated ANNMG model was then used to generalize mineral grades. The original and generalized assay values were combined and fed to geostatistics in order to develop the geological reserve model, which consists of blocks with values of mineral grades and economic costs, used in mine design and operation scheduling.

This dissertation consists of six chapters.

Chapter 1 discusses the importance of integrating ANNs with geostatistics for mineral reserve estimation. It introduces previous studies on ANNs, geostatistics and mine design, planning and operation scheduling.

Chapter 2 details the geological characteristics of the Marampa iron deposit located in Sierra Leone. This deposit was used to document the case study. Sierra Leon forms part of the West African Craton, and about 75% of the outcrops are older than 2.1 Billion years. The rocks have been affected by many tectonic events and the structures produced have been used to unravel the geological history of the country. The geology,

like in other parts of West Africa consists of a basement complex, supracrustal rocks, and intrusive granites. It further described the location of the project area from which a set of exploration data from the Iron Ore deposit which lies within the supracrustal rocks of the Marampa schist formation, which hosts a primary quartz-hematite schist horizon with a thickness of up to 65m, located in Sierra Leone.

Chapter 3 describes analyzing the drillhole data comprising of 14982 composite samples using the Geostatistical Software Library known as GSLIB. The GSLIB was used to study the spatial variation in the data from which three directional (0º, 45º and 90º) variograms were constructed. Based on the analysis, the inference was made about the data. It did not deviate severely from normality and stationarity, and it exhibits an asymmetric distribution with a negative skew. The drillhole data sampling and preparation process was validated with duplicate samples for analysis. The correlation coefficient (R^2) of the laboratory duplicates for Fe_2O_3%, Al_2O_3% and SiO_2% were 0.991, 0.988 and 0.967, respectively. These values of correlations indicate confidence in the sample analysis process.

Chapter 4 details the application of the ANNMG model which was trained using the Levenberg-Marquardt backpropagation algorithm for mineral reserve estimation. The number of drillholes that contributed to the model's training, testing and validation were 269, 135 and 135 respectively. The model's performance was assessed by two estimation errors: the mean squared error (MSE) and R^2. The model's MSE values were 0.204, 0.209 and 0.209, and the R^2 values were 0.893, 0.881 and 0.881 for training, testing and validation data respectively. The overall R^2 was 0.889. It was proven that the ANNMG model could explain 88.9% of the variability as overall. For sensitivity and validation purposes, the impact of utilizing fewer drillholes in the training process was studied using 150 drillholes for training and 60 drillholes each for testing and validating the model. The average grade computed by the ANNMG model using 269 drillholes for training was 0.44% lower than that of the 539 drillhole data while using 150 drillholes was 0.65% lower.

Chapter 5 introduced some simulation results of open-pit mine design and scheduling using the Best Positive Inverted Truncated Cone (BPITC) method. The BPITC method, developed by Dindiwe et al. (2001), is not a mathematical formulation but rather a sequential approach to mine optimization involving calculations leading to optimality. It is purely based on the principle of the moving cone technique with excavations from bottom to top instead of the reverse called Best Positive Moving Cone (BPMC). The simulation results provided the production schedules and produced a stable life of mine results that minimize the deviation from ore and waste production by handling the uncertainty using the BPITC method. These were achieved by defining a fixed ultimate pit based on a single estimated orebody model then apply the fixed pit limit to the simulated orebody models, and optimize the simulated orebody models individually. The Net Present Value (NPV) for optimizing the individual simulated orebody models was found to be 16% greater than the NPV for the first method of applying the fixed pit limit to the simulated orebody models. Also, BPITC, when compared with the BPMC method, was found to be about 10% larger regarding total tonnage. This difference adds approximately 7% of additional NPV to the mining. The differences reported between the BPITC and the BPMC methods were due to the different scheduling patterns.

Chapter 6 is a summary and a conclusion of the findings of the research and future studies on optimizing operations from mine to refineries, incorporating the use of artificial intelligence technologies.