Journal of Mineral Resources Engineering, 8(2): 19-40, (2023)

Imam Khomeini International University
Vol. 8, No. 2, Summer 2023

نشریه مهندسی منابع معدنی
Journal of Mineral Resources Engineering
(JMRE)

Research Paper

Estimating the Reserve of Lake- Siah Iron Ore Body by Geostatistical and Artificial Network Methods

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Received: 02 Oct. 2021 **Accepted: 25 Dec. 2021**

Abstract: Investments and progress of mining projects depend on the quantity and quality of mineral resources and reserves; therefore, it is significant to know the reliability of the ore deposit estimation based on various methods. This research has investigated the role of geostatistics and artificial neural networks in modeling, estimating the concentration of exploration blocks, and estimating mining reserves. Spatial distribution modeling of iron values has been performed using three methods of ordinary kriging, Gaussian simulation, and artificial neural networks. To construct the block model of ore deposit, 29 exploratory boreholes with an average depth of 142.75 meters and a total length of 4139.9 meters were used. After drawing the variograms, the search ellipse was calculated, and a 3D model was obtained to estimate the concentration by ordinary kriging and Gaussian sequential simulation methods. Also, modeling and estimating the concentration was done by the artificial neural network method. Results showed that the artificial neural network technique has high validity. Also, due to its ease of use and no need for extra variographic calculations can be an appropriate alternative to geostatistical and simulation approaches. Finally, based on different cut-offs, the concentration-volume curve was drawn. The results show that this ore body has 439 million tons of ore with an average concentration of 42 % per 20% cut-off concentration.

Keywords: : Ordinary kriging, Sequential Gaussian simulation, Artificial neural network, Concentration-volume curve, Lake-siah.

How to cite this article
Mousavi, S. J., Shayestehfar, M. R., and Maarefvand, P. (2023). *"Estimating the reserve of Lake- Siah iron ore body by geostatistical and artificial network methods"*. Journal of Mineral Resources Engineering, 8(2): 19-40.
DOI: 10.30479/JMRE.2022.16295.1549

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INTRODUCTION

Ore concentration is one of the main variables that characterize the value of an orebody. Almost every mining project begins with determining ore concentration distribution in 3D space, a problem often reduced to modeling the spatial variability of ore concentration values [1,2]. Spatial modeling of the concentration variability in a deposit directly impacts the evaluation of recovery functions, such as the volume, metal quantity, and mean concentration above cut-offs [3]. A reliable reserve and concentration estimation of an ore deposit will help the industries to make an investment decision on mining projects [3]. Thus, ore concentration estimation is a significant factor of ore deposit value evaluation and profitable mining operations. Also, choosing the proper estimation method for optimal reserve with the minimum error is major in mining engineering operations.

The major problem of concern to the mining engineers is selecting an appropriate method to estimate the ore concentration and reserve estimation. Because an ore deposit has a complex structure with many parameters involved, the most significant parameter is the distribution of ore concentrations.

In mining studies, geostatistical techniques are preferred due to concentration and recoverable reserve estimations. Geostatistical methods are more suitable, reliable, and preferable for modeling and the spatial distribution of the ore concentrations [3-5]. Various researchers [6,7] have successfully adopted this method for concentration/reserve estimation of different deposits around the world. Nowadays, geostatistical simulation and neural networks (NNs) methods are the prevalent techniques used for ore concentration estimation. However, these models work under fundamentally different frameworks. Geostatistical simulation is a technique that reproduces spatial heterogeneity of datasets. Many algorithms such as sequential Gaussian simulation (SGS) have been used for simulating continuous regionalized variables in the last three decades. SGS is fast and has shown good efficiency in the implementation [8]. Kriging is the base of most geostatistical simulation approaches, including sequential Gaussian simulation, widespread in earth science applications [9]. Moreover, they are linear models based on the local neighborhood structure. On the other hand, a NN has a non-linear distribution, which is robust for noisy and extreme-value data.

METHODS

Techniques used in research, such as geostatistics, SGS, and ANN are introduced. The chief venture in ordinary kriging is to build a variogram from the dissipate point set to be interpolated. A variogram comprises two parts: an experimental variogram and a model variogram. Geostatistical simulation methodologies allow the generation of several results with the same probability of occurrence, which can then together be treated for local uncertainty evaluation purposes (SGS).

In this research, we investigate the estimation of ore concentration distribution to identify abilities and weak points for concentration variation modeling. Geostatistical and machine learning approaches such as neural networks are used to estimate the iron concentration in an orebody. The performance of these methods is compared to each other. We compared geostatistical and ANN methods for estimating the concentration and reserve of an orebody. The effectiveness of these techniques is illustrated in the estimation of iron concentration values and reserve in the Lake Siah orebody in central Iran. Subsequently, the results of these methods are compared, and the observed differences are evaluated and analyzed.

FINDINGS AND ARGUMENT

Spatial distribution modeling of iron ore has been carried out employing geostatistics techniques such as OK and SGS. Also, non-linear modeling has been performed using ANN that provided an alternative option for concentration estimation in the study area. The study aimed to compare the estimates of OK, SGS, and ANN and identify which technique produces a more accurate estimate of the mineral reserves. This study had tested using drill hole data from a real undeveloped deposit in Iran. Block value prediction obtained employing kriging, simulation, and ANN model have been compared for the suitability of the methods. Experimental variograms of Fe concentration have been calculated in different directions to investigate anisotropy. Based on the results, the orebody was anisotropic, and the anisotropy type was geometric.

CONCLUSIONS

A comparison of Fe predicted values obtained by application of kriging, simulation, and ANN models more or less maintain similar distribution patterns in all three models that are close to the actual data. The biggest challenges in using geostatistics lie in the failure in variogram modeling, non-stationarity, and normality of the data. SGS had a less smoothing effect on data than OK and honors spatial variability of data. Hence it provides a better estimation of mining blocks. For these reasons, SGS preferred the OK for ore and waste selection. Also, this study showed that the right choice of the training algorithm grants maximizing the predictive capability of the ANN models. The LM method had been recognized as the best training algorithm for concentration predictions. The precision of predictive ability was measured for concentration estimation. Results showed when the ANN model is available, can provide a significant advantage in reserve estimation. Also, the results obtained from the concentration distribution showed that neural networks offer a valid alternative approach to the problem of ore concentration estimation while requiring considerably less knowledge and time. Consequently, we suggested carrying out the concentration modeling employing these three approaches to obtain alternative scenarios for improved mine planning in ore deposits.

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