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An Integrated Geo-Statistical Methodology for an Optimum Resource Estimation of Angouran Underground Mine

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Abstract

Resource estimation and determining the grade distribution is one of the most important stages in planning and designing the open-pit and underground mines. In this work, a new mythology is used for resource estimation of the Angouran underground mine based on the optimized integration of the indicator kriging (IK), simple kriging (SK), and inverse distance weighted (IDW) methods. For this purpose, waste blocks are first removed from the block model using the IK method. Then the amount of mineral resource is estimated using the SK and IDW methods. Indeed, variograms are developed to estimate the grade of zinc minerals in the three used methods. Variograms analysis in three directions prove that the studied resource is anisotropic. Also the validation results confirm that the correlation coefficients between the measured and estimated zinc values by the SK and IDW methods equal to 0.76 and 0.75, respectively. Knowing this satisfactory result, a 3D model of the resource is prepared using the IK method, in which the ore and waste sections of the Angouran underground mine are separated definitely. According to the above methodology, the calculated resource of the Angouran underground mine using the SK method is achieved 1373962.5 tons with an average grade of 30.11%, whereas the estimated amount of this resource is attained 1349325 tons with an average grade of 31.88% using the IDW approach. The verification results show that the suggested methodology based on the optimized integration of the IK, SK, and IDW methods can be successfully applied for resource modeling and grade estimating of the Angouran underground mine.

1. Introduction

Resource estimation is a main process in the mining operation that provides the foundation for the feasibility study of a resource whether it has the potential to become a mine or not. Therefore, the cost-effectiveness of a deposit is extremely influenced by the correctness of the resource estimation. In fact, a precise resource estimation can assist the governments, investors, and industries to make an accurate decision for mine investment objectives. On the other hand, precise resource estimation is commonly governed by the appropriate utilized estimation method, which is compatible with the mineral resource conditions such as the geological, structural, and geometrical features. Indeed, the main concern of mine engineers is the selection of an appropriate technique for resource estimation since applying an inappropriate technique in this stage can cause about ±50% error. Therefore, it can be concluded that the mine's future efficiency is extensively associated with the estimation of the resource quantity (tonnage) and quality (grade) in this process [1–4].

Various techniques such as conventional, geo-statistical, and artificial intelligence methods were applied for resource estimation so far [5–9]. In the conventional approaches like the cross-section methods, random distribution is assumed, in which the sample amounts are independent from each other. The common capability of this method is providing the total estimation of a resource. However, it is not capable in determining the

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amount of mineralization continuity between a definite point and possible indefinite points. Therefore, the conventional approaches frequently cause over-valuation of possible wasteful deposits and under-valuation of probable economic deposits [10, 11]. Unlike the conventional approaches, samples in an ore body are spatially associated with each other in geo-statistical models. In these methods, the resource estimation is performed based on the variography and kriging analyses. In variography analysis, the number of interdependencies among the detected amounts of an ore resource is measured using an analytical approach. As the most used estimation techniques in geo-statistical modeling, the kriging techniques (i.e. ordinary kriging, universal kriging, indicator kriging, cokriging, etc.) are the universal resource estimation methods that assign the optimum weights to minimize the estimation error. Geo-statistical methods are the most desired resource estimation techniques for the mine exploration engineers due to their unique capabilities in recognizing the existing three-dimensional relationships among the adjacent samples/points in terms of the quantitative values [12–15]. These techniques have been efficiently applied for ore resource estimation by numerous investigations that are briefly outlined here.

Tercan and Karayigit [16] applied a variance-based approach to evaluate a lignite deposit based on the borehole data. Misra *et al*. [17] used the neural network and geo-statistical methods to predict arsenic resource estimation. The results of the above study proved that the geo-statistical method has a better capability than the neural network approach. Heriawan and Koike [18, 19] evaluated the coal deposit quality and quantity using the different appropriate geo-statistical methods based on the seam geometry and coal chemical properties. Tahmasebi and Hezarkhani [20] used neural network, genetic algorithm, and fuzzy logic for resource estimation, and confirmed that the genetic algorithm provided the better performance than the artificial neural network and fuzzy logic techniques. Olea *et al*. [21] utilized several geo-statistical approaches for uncertainty estimation in calculating the coal value inside a lignite reservoir. Shahbeik *et al*. [22] utilized the ordinary kriging and inverse distance weighted methods to estimate an iron deposit, and proved that the ordinary kriging method has a higher accuracy than the inverse distance weighted method. Thakur *et al*. [23] utilized the geo-statistical models for minable resource estimation of a beach-sand deposit and found that the used models are completely reliable for this aim. Daya and Bejari [24] applied simple and ordinary kriging techniques to evaluate a copper deposit, and concluded that the simple kriging approach estimates smoother results but it is less accurate than the ordinary kriging method. Daya [25] used the ordinary kriging method to estimate the copper resources, and proved that the ordinary kriging technique is a suitable method to estimate the vein-type deposits. Thakur *et al*. [26] used a combination method based on the spatial method and the kriging technique for resource estimation, and proved that the suggested hybrid approach can improve the accuracy of resource estimation. Jafrasteh *et al*. [27] applied neural network and geo-statistical methods to estimate the copper grade, and demonstrated that the geo-statistical method has the precise performance than the neural network model. Rahimi *et al*. [28] utilized Gaussian kriging and Gaussian sequential simulations for resource estimation, and found that their suggested simulations are suitable for shallow-depth deposits. Rezaei *et al*. [29] performed the resource estimation based on the three-dimensional grade simulation of an iron ore deposit, and concluded that the used 3D model helps the simplifying of existing complexity in the resource modeling and achieving the spatial information of resource. Arinze *et al*. [30] developed a geometrical method for resource estimation in a zinc-lead deposit, and confirmed its appropriateness. Based on the geometrical and geo-statistical methods, Afeni *et al*. [11] performed a limestone resources estimation, and proved that geometrical methods can be effective for tonnage estimation. However, the geo-statistical method has a logical function in resource modeling, and it is a more suitable and reliable for qualitative estimation of limestone resources. Zerzour *et al*. [31] conducted the geo-statistical modeling to evaluate a complex iron deposit successfully. Uyan and Dursun [32] applied geo-statistical modeling and geographic positioning system for resource estimation of a lignite deposit effectively. Dinda and Samanta [33] conducted some geo-statistical and simulation-based models to evaluate a copper resource, and proved that simulation models have higher precision than the geo-statistical approaches. Madani *et al*. [34] conducted a copper deposit estimation using geo-statistical modeling and multinomial logistic regression. They found that their proposed methods are able to estimate the expected non-stationary characteristics of the deposit and its quantitative values and superior in modelling heterogeneous geo-domains.

In this research work, a new methodology is used for zinc resource estimation in the Angoran underground mine. In the applied methodology, the indicator kriging method, simple kriging, and inverse distance weighted methods are integrated and optimized to achieve the optimum outputs. It should be noted that the resource estimation of the Angoran underground mine is investigated for the first time in this work, and will be considered as the basis for mine planning and scheduling.

2. Case Study

The Angouran mine is considered as the case study in this work. This mine is located in a mountainous area with an average altitude of 2950 m above the sea level, 135 km SW of Zanjan, and 450 km NW of Tehran. The geographical coordinates of the mine are 47-24′ east longitude and 36-37′ north latitude. The Angouran mine is a geologically part of the Urmia-Dokhtar zone, which is located between the Zagros and western sections of Central Iran. The mine is structurally located at the central section of the Angouran anticline. Most of the mine rock floors are made of graphite metamorphic limestone. In the mine area, effect of folding is reduced by passing the carbonate section to the metamorphic rocks in mine west. The most of mineral deposits are formed inside the central part or the anticline core. This anticline is then transformed into an inverted anticline during the orogenic movements of the Late Alps, in which its inclination is in the northwest direction, and the trend of the fold axis is almost justified by the anticline at the east and west. The host rock of the Angouran mineral zone is located inside a metamorphic complex from the Neoproterozoic to the Cambrian and the lower Miocene periods. It is deformed by tensional processes in this area and formed a collection of amphibolite, serpentinite, gneiss, mica-schist, calcite, and crystalline limestone or marble rocks. The mentioned marble rocks are available in some areas as an interlayer with amphibolite, gneiss, and mica-schist having a thickness of 300 m in some regions. The most important ore-bearing horizons of the Angouran resource are formed in the top units of crystalline limestone with a maximum length of 700 m and a maximum width of 600 m. The ore-bearing area is also affected by a weak folding passing through the carbonate units to the metamorphic rocks. Here, the minerals are approximately located in the central section or in the core of anticline (Figures 1 and 2). The Angouran mine faults are generally divided into two categories including main faults and sub-faults. The main faults have EW and NW-SE directions with a longitudinal extension for more than 200 m. The sub-faults have a longitudinal direction for less than 50 m that cause some ground displacements with different extensions in the area. According to the field surveying, it is proved that most changes in geological sections are occurred by major faults with EW direction [35–37]. From the mineralization viewpoint, there are both oxide and sulfide mineralization types in the Angoran mine (in both surface and underground sections). However, most of the oxide mineralization was located at the surface section, which was extracted during the past years. In practice, more than 95% of the Angoran underground mine resource is of the sulfide type. Accordingly, the total amount of resource in the Angouran underground mine is considered as sulfide, and the negligible oxide amount was ignored.

3. Dataset

The resource of Angouran underground mine is investigated in the current work based on the information of 62 boreholes with a total drilling length of 1936 m (Figure 3). As seen in this figure, the drilling network does not follow a particular trend and the distance between boreholes is irregular, and the length of acquired core samples from the boreholes is unequal. Since working on the specimen with an equal length is very important in resource estimation, database was processed and irregular samples are equated with equivalent lengths, according to Daya [24]. Frequency of the length of core specimens of the boreholes is plotted in Figure 4. According to this figure, specimens with 2 m length have the highest frequency, and thus it is used for composition objectives. Statistical analysis is used to provide the normality or non-normality of data, a single community or multi-community study, and the presence or absence of trends in database. The results of the above statistical analyses are demonstrated in Table 1 and Figure 5. Since the database includes two parts, i.e. ore and waste, it is converted to a community (Figure 6). Also it is proved that there is no specific trend in zinc database, and the concentration of zinc is not associated with the coordinates of boreholes (Figures 7–9). Since the LK and IDW methods are used in this study, thus normalization of the raw database is not required.

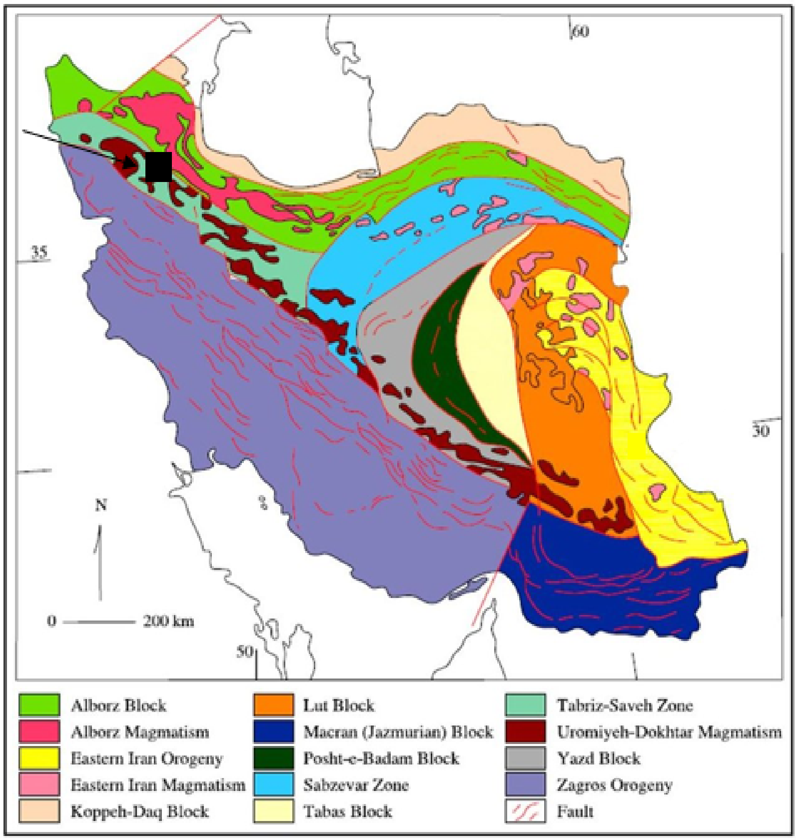


Figure 1. Location of Angouran mine on the structural chart of Iran.

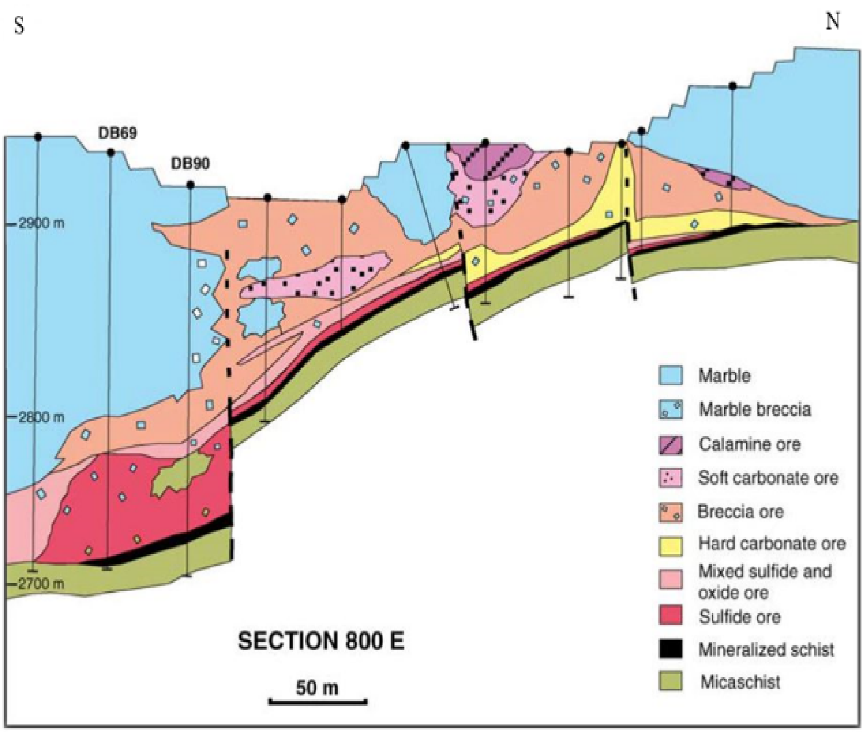
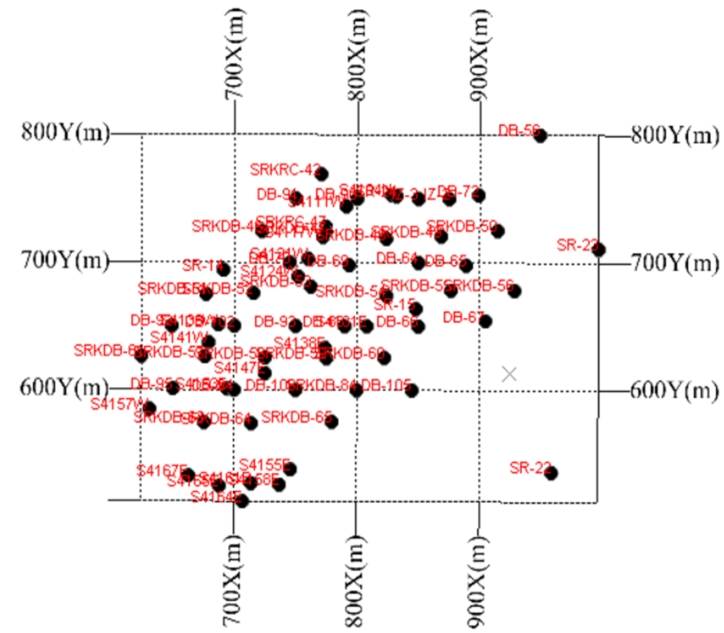
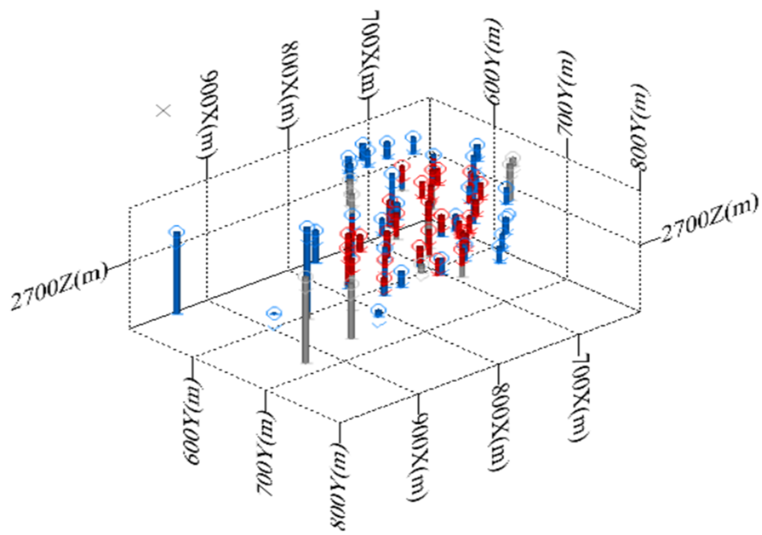


Figure 2. North–South geological section of the Angouran mine resource.



(a)



(b)

Figure 3. Grid drilling at Angouran mine resource: (a) 2D representation; (b) 3D representation.

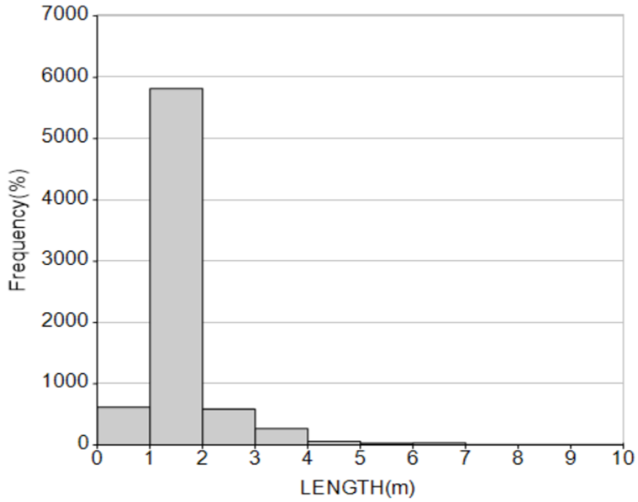


Figure 4. Frequency of core length in the database.

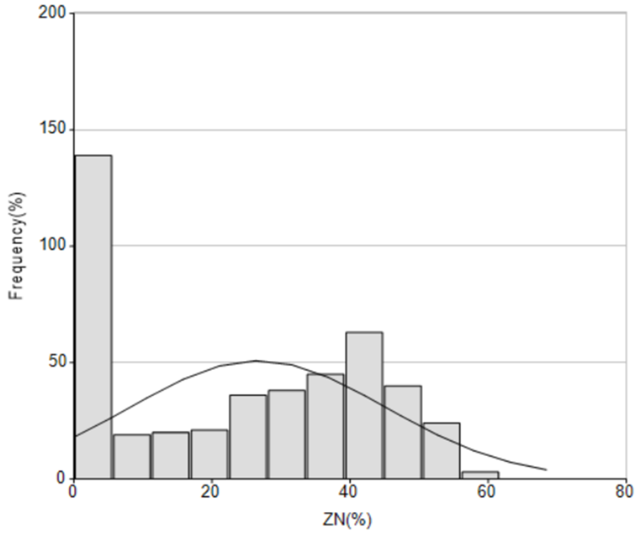


Figure 5. Histogram of Zn database.

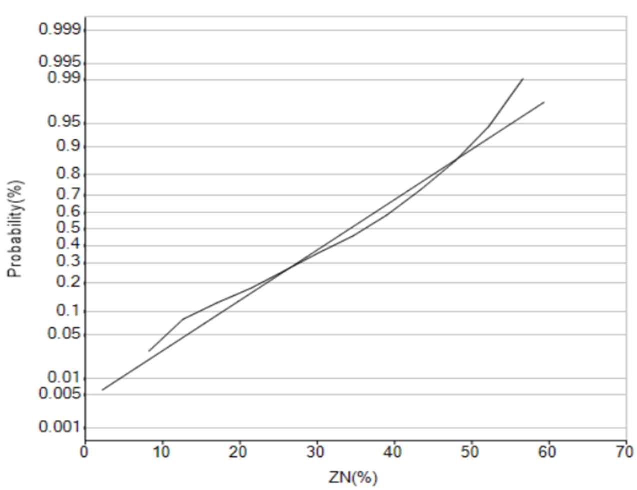


Figure 6. Transforming the mineral data into a community.

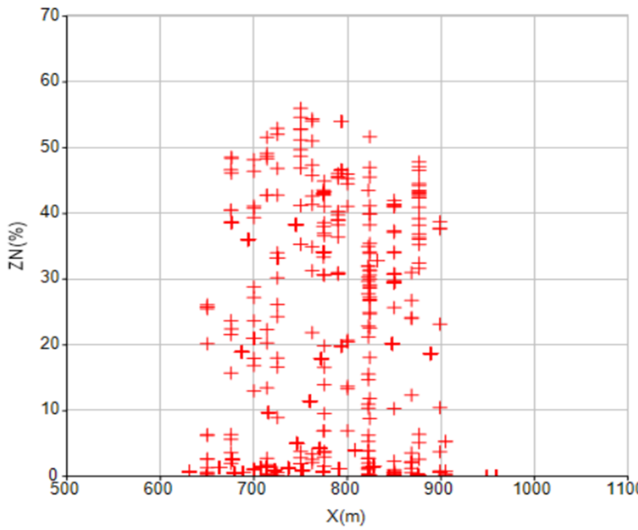


Figure 7. Variations of Zn condensation in east–west direction.

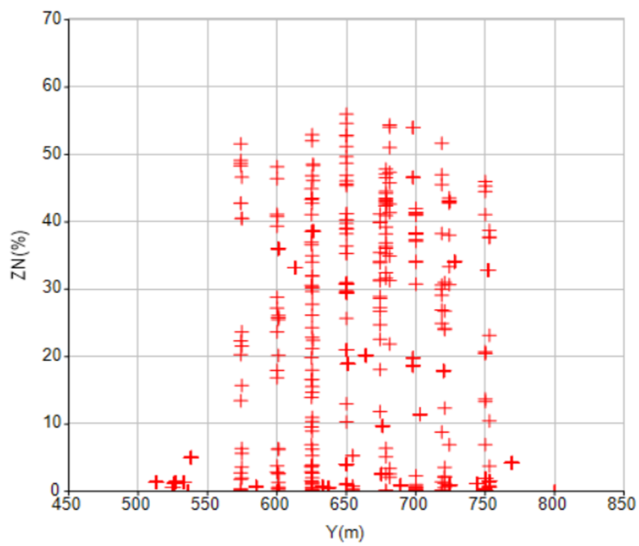


Figure 8. Variations of Zn condensation in north–south direction.

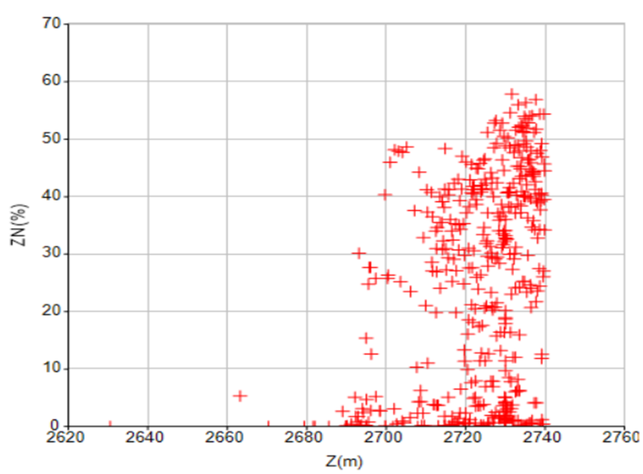


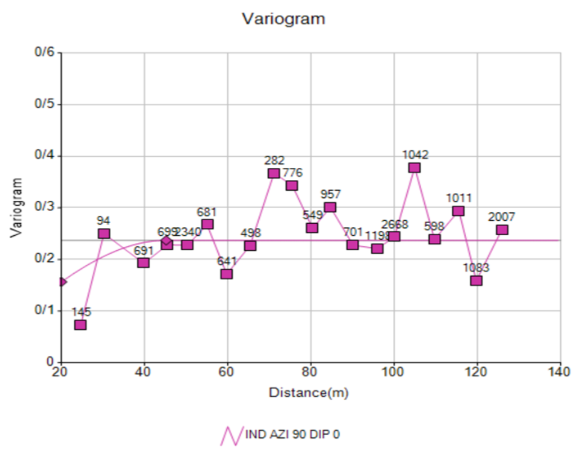
Figure 9. Variations of Zn condensation in depth direction.

Table 1. Statistical characteristics of Zn raw database.

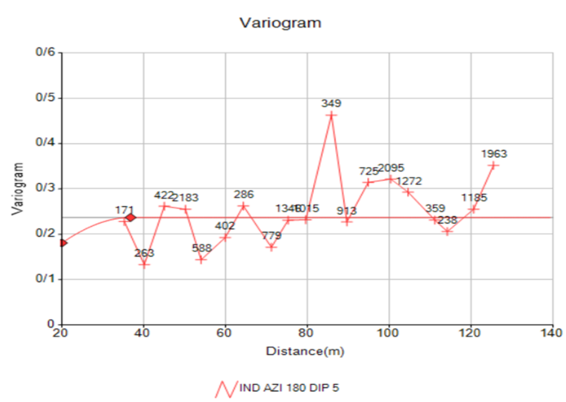
Parameter	Zn
Mean	24.006
Variance	339.65
Std. deviation	18.43
Minimum	0.01
Maximum	57.88
Skewness	-0.015
Kurtosis	-1.49

4. Variography

Variogram analysis is very important for structural simulation and spatial visualization. The Variography is an important technique for spatial interpolation that includes the important variables for geostatistical modeling [22]. Variogram models include simple models comprising exponential, spherical, Gaussian, linear, and power types [35]. The most commonly used technique in the mining operation is the spherical model. Accordingly, a spherical model is used in this research work. Based on this model, variography was performed for all three used methods including indicator kriging (Figure 10 and Table 2), simple kriging (Figure 11 and Table 2), and inverse distance weighted (Figure 12 and Table 2). As it can be seen from these analyses, the obtained variograms have the same sill and Nugget but different radii effects. This is confirmed by the existence of geometric anisotropy in the data.



(a)



(b)

Figure 10. Trial variogram and compatible models for IK method (a) Azimuth = 90 and Dip = 0, (b) Azimuth = 180, and Dip = 5.

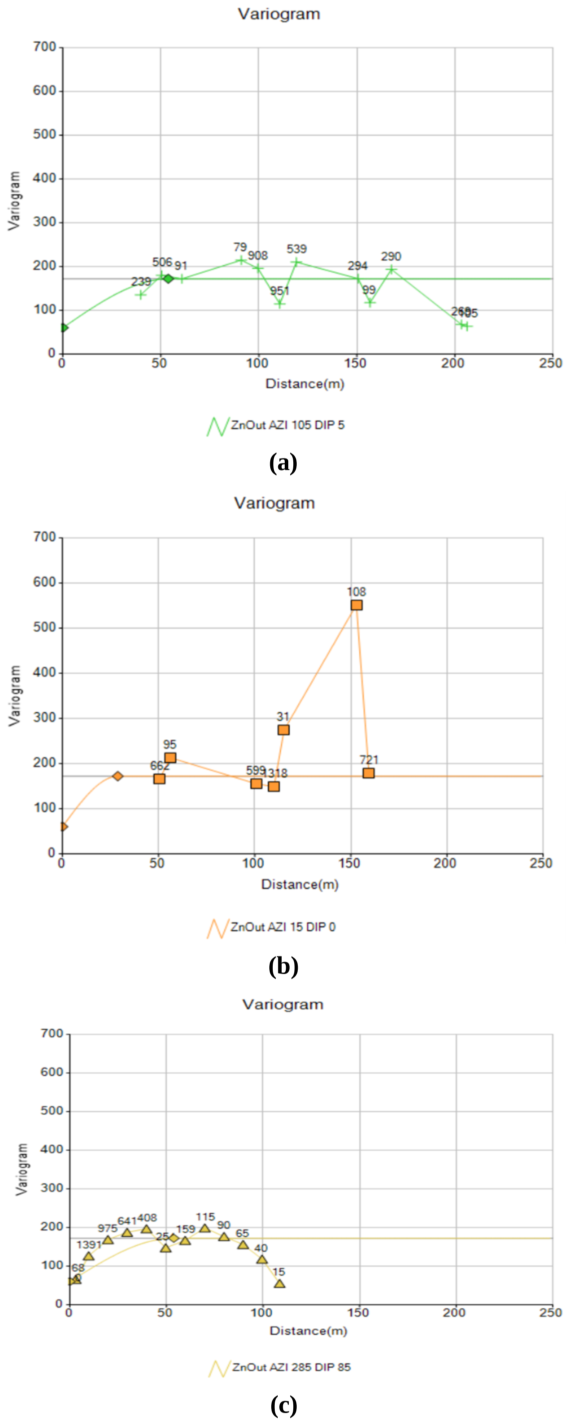
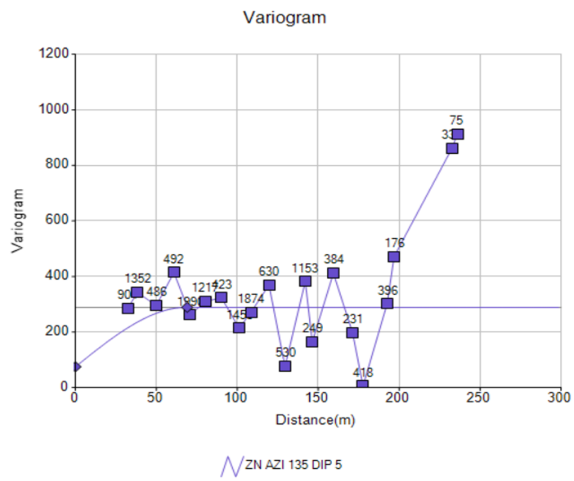
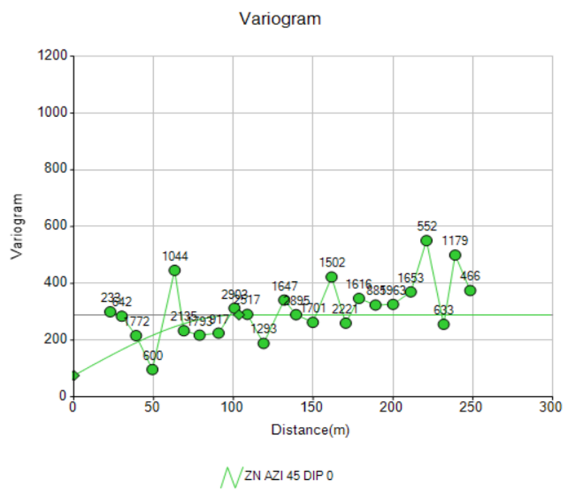


Figure 11. Trial variogram and compatible models for SK method (a) Azimuth = 105 and Dip = 5, (b) Azimuth = 15 and Dip = 0, (c) Azimuth = 285 and Dip = 85.



(a)



(b)

Figure 12. Trial variogram and compatible models for IDW method (a) Azimuth = 135 and Dip = 5, (b) Azimuth = 45 and Dip = 0.

Table 2. Result of directional variograms.

Variables	Range (m)	Sill (%)	Nugget effect	Direction	Variogram model
IK	36.7 45.1 1	0.237	0.024	180/5 90/0 -	Spherical
SK	54.3 28.9 53.7	172	60.41	285/85 105/5 15/0	Spherical
IDW	68.4 102.9 1	288.8	75	135/5 45/0 -	Spherical

5. Results and Discussion

5.1. Block modeling

Determining the various dimensions in the 3D block modeling is very important for resource estimation, and consequently for mine planning. There exists a general method for determining the dimensions of blocks based on the geometric characteristics of the resource and drilling network. Based on this method, the dimensions of blocks are calculated as follows [22]:

(a) As the drilling network is not regular, the length of each block is considered equal to 10 m, which approximately equals to the half of center distance between the boreholes along the maximum of resource variability.

(b) Since the drilling network is not regular, the width of each block is considered equal to 10 m, which approximately equals to the half of center distance between the boreholes along the maximum of resource variability.

(c) The height of each block is considered equal to 10 m, due to the ore persistence and the thickness of the waste.

After identifying the optimum size of each block, a 3D block model of the resource is constructed and represented in Figure 13.

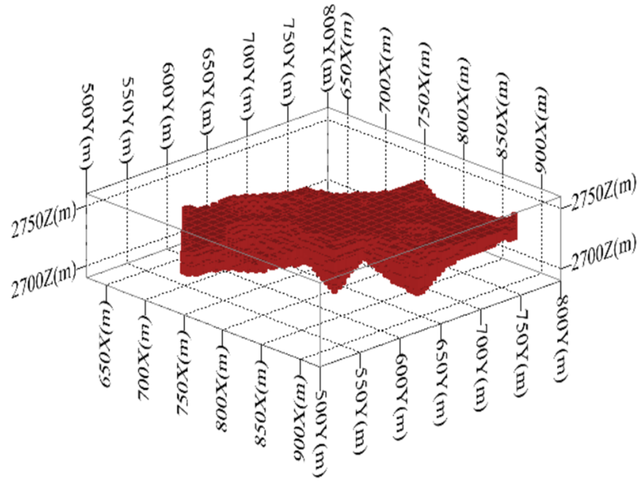


Figure 13. 3D block model of the Angouran mine resource.

5.2. Removal of waste blocks using IK method

The waste blocks in the final block model are removed using the IK method. In the removal of waste blocks using the IK method, the threshold value of Zn is considered 0.68% according to the policy of Angouran mine management. After estimating the indicator for the data with considering Zn threshold value equal to 0.68%, the blocks with higher and lower grades than the 0.68% are considered ore and waste blocks, respectively. Indeed, the determined waste blocks by IK method are permanently deleted in further estimations. Figure 14 demonstrates the total data blocks comprising ore and waste blocks and Figure 15 shows only the data ore blocks.

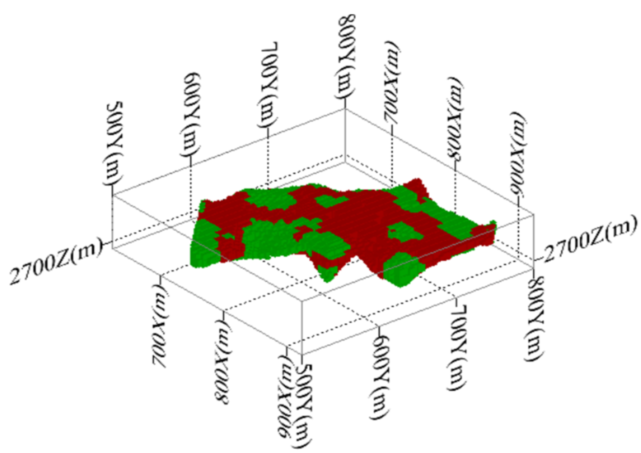


Figure 14. Total ore and waste blocks of the Angouran mine resource.

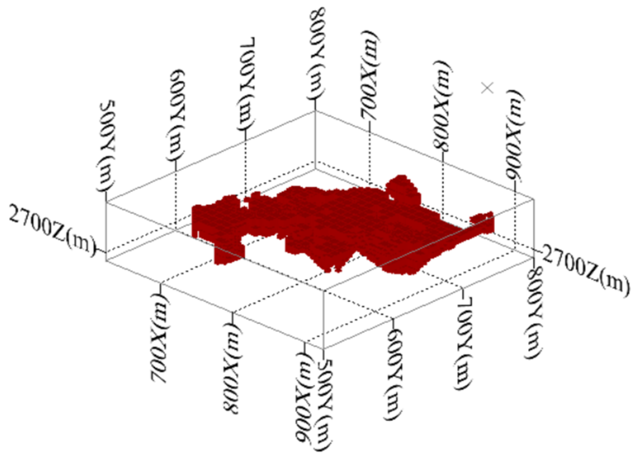


Figure 15. Ore data blocks of Angouran mine resource.

5.3. Resource estimation using SK and IDW methods

According to the variography analyses and constructed 3D block model, the amount of zinc tonnage inside the resource is estimated using the SK and IDW methods. For this resource estimation, grade-tonnage curves are used. These curves can help the mine planners in order to correctly define the long-term, medium-term, and short-term variables for mine planning and scheduling. Figure 16 and Table 3 show the grade-tonnage results of SK method, and Figure 17 and Table 4 represent the grade-tonnage factors of the IDW method.

Table 3. Grade-tonnage results of SK method.

Metal content (ton)	Cut off (%)	Average grade (%)
1373962.5	10	30.11
1354556.25	15	30.34
1268662.5	20	31.18
1097718.75	25	32.44
681243.75	30	35.37
308137.5	35	39.08
104625	40	42.29
6750	45	45.21

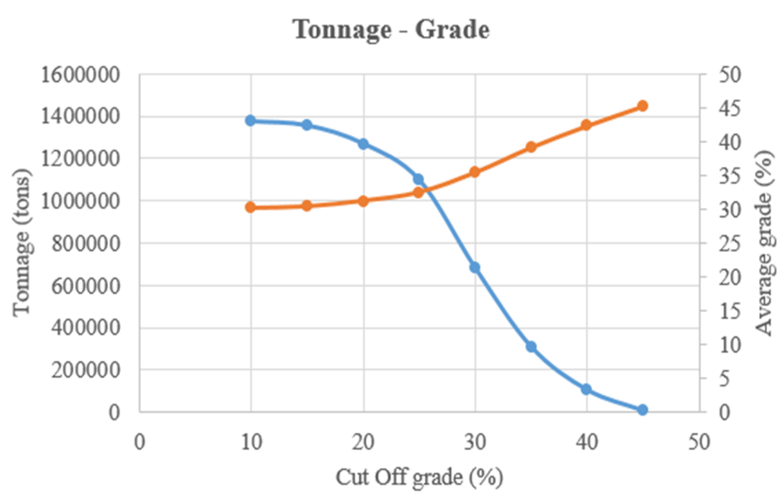


Figure 16. Curve of grade-tonnage resulted from SK method.

Table 4. Grade-tonnage results of IDW method.

Metal content (ton)	Cut off (%)	Average grade (%)
1349325	10	31.88
1330762.5	15	32.14
1279631.25	20	32.72
1115775	25	34.11
788062.5	30	36.78
433350	35	40.38
210093.75	40	43.71
51468.75	45	47.45
8100	50	50.79

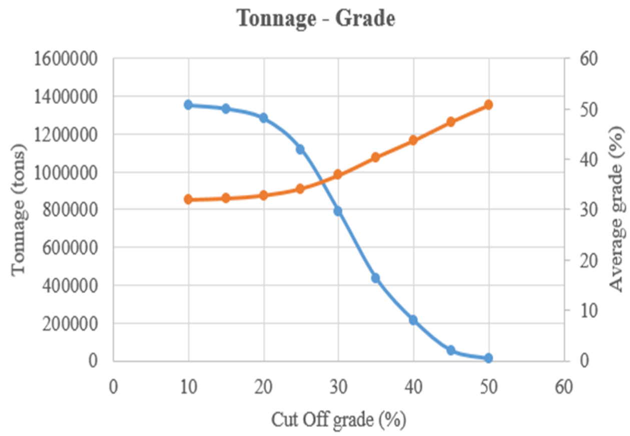


Figure 17. Curve of grade-tonnage resulted from IDW method.

6. Result Validation

After estimating the Zn grade of all blocks, statistical methods and actual data are used for result validation. Indeed, the adaptation of boreholes and estimated blocks is determined. In order to evaluate the result validation, the estimated blocks grades are first compared with the grades of boreholes using statistical methods. Indeed, statistical parameters of the Zn grade of total blocks are compared with the borehole data. Statistical comparison results of the IK and IDW methods with borehole data are given in Table 5. As it can be seen from this table, the results are reasonably close together and in accordance with the measured data. This validation indicates that the outputs of this study are acceptable for the future planning and scheduling in the Angouran underground mine. For further validations, the estimated grades of blocks are compared with the grade of the field boreholes based on the real comparison method. Figures 18 and 19 show the correlation diagrams between the field boreholes and the estimated blocks by the SK and IDW methods, respectively.

Table 5. Statistical characteristics resulted from SK and IDW methods.

Statistical index	Borehole data	SK	IDW
Minimum	5.65	10.99	12.01
Maximum	54.6	45.64	51.25
Mean	30.68	29.01	31.01
Variance	152.2	41.03	52.5
Std. deviation	12.33	6.4	7.24
Std. error	0.65	0.2	0.24
Skewness	-0.16	0.08	0.13
Kurtosis	-0.91	0.005	-0.09
Geometric Mean	27.57	28.26	30.12
Log-Est Mean	31.3	29.04	31.06

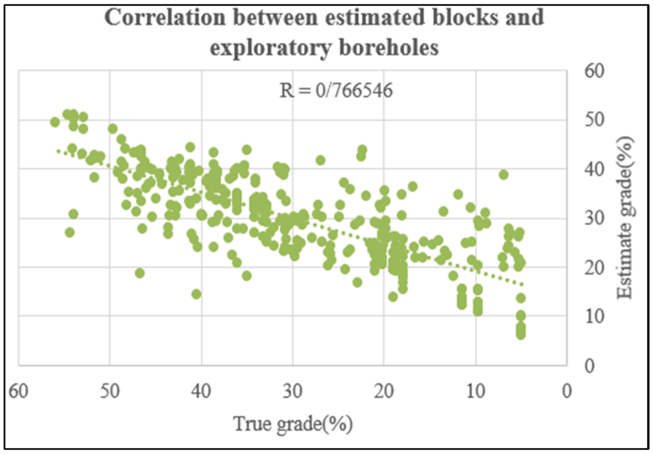


Figure 18. Cross-validation chart of measured and predicted Zn values form SK method.

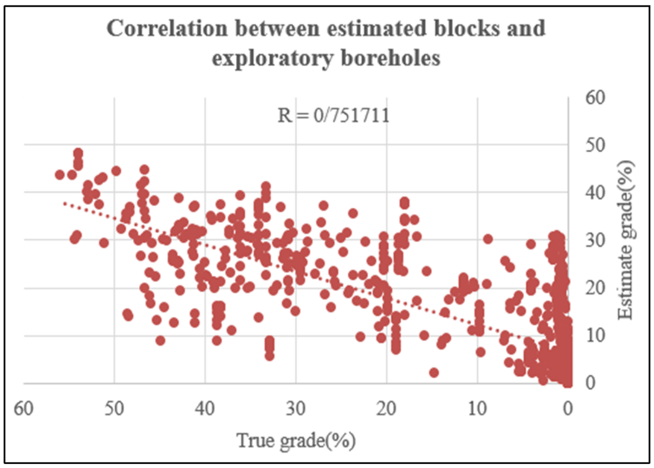


Figure 19. Cross-validation chart of measured and predicted Zn values form IDW method.

7. Conclusions

Selecting the optimum method with minimum error for resource estimation is very important in mining engineering. In this research work, optimized integration of the IK, SK, and IDW methods was applied for resource estimation of the Angouran underground mine. The resource values were calculated using the SK method with a cut-off grade of 10%, a value of 1373962.5 tons, and an average grade of 30.11%. This resource is also estimated by the IDW method with a cut-off grade of 10%, a value of 1349325 tons, and an average grade of 31.88%. It can be concluded that the estimated resources from both the SK and IDW methods are in close agreement. Statistical validation of the obtained results proved that the obtained results by both SK and IDW methods were acceptable. Moreover, the obtained correlation coefficients between the estimated blocks and the exploration boreholes for the SK and IDW methods are achieved equal to 0.76 and 0.75, respectively. This means that both estimates of SK and IDW are reliable, and their results can be applied for future planning objectives. According to the obtained results, it can be concluded that both the SK and IDW methods are acceptable for resource estimation in the Angouran underground mine, and their results can be used in future economic decisions and mine scheduling.

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References

[1]. Dominy, S.C., Noppe, M.A. and Annels, A.E. (2002). Errors and uncertainty in mineral resource and ore reserve estimation: the importance of getting it right. Exploration and Mining Geology, 11 (1-4): 77–98.

[2]. Hajsadeghi, S., Asghari, O., Mirmohammadi, M., Afzal, P. and Meshkani, S.A. (2020). Uncertainty-Volume fractal model for delineating copper mineralization controllers using geo-statistical

simulation in Nohkouhi volcanogenic massive sulfide deposit, Central Iran. Bulletin of the Mineral Research and Exploration, 161 (161): 1–11.

[3]. Zerzour, O., Gadri, L., Hadji, R., Mebrouk, F. and Hamed, Y. (2021). Geostatistics-based Method for Irregular Mineral Resource Estimation, in Ouenza Iron Mine, Northeastern Algeria. Geotechnical and Geological Engineering, 39(5): 3337–3346.

[4]. Kerbati, N.R., Gadri, L., Hadji, R., Hamad, R. and Boukelloul, M.L. (2020). Graphical and numerical methods for stability analysis in surrounding rock of underground excavations, example of Boukhadra Iron Mine NE Algeria. Geotechnical and Geological Engineering, 38, 2725–733.

[5]. Soltani, F., Moarefvand, P., Alinia, F. and Afzal, P. 2019. Characterizing Rare Earth Elements by coupling multivariate analysis, factor analysis and geo-statistical simulation; case-study of Gazestan deposit, central Iran. Journal of Mining and Environment, 10 (4): 929–945.

[6]. Yasrebi, A.B., Hezarkhani, A., Afzal, P., Karami, R., Eskandarnejad Tehrani, M. and Borumandnia, A. 2020. Application of an Ordinary Kriging-Artificial Neural Network for Elemental Distribution in Kahang Porphyry Deposit, Central Iran. Arabian Journal of Geosciences, 13, 748 (1–14).

[7]. Sotoudeh, F., Ataei, M., Kakaie, R. and Pourrahimian, Y. (2020). Application of Sequential Gaussian Conditional Simulation to Underground Mine Design Under Grade Uncertainty. Journal of Mining and Environment, 11 (3): 695–709.

[8]. Shafayi, S.H. and Mohammad Torab, F. (2022). Ore Deposit Boundary Modification in Afghanistan Aynak Central Copper Deposit using Sequential Indicator Simulation and Indicator Kriging. Journal of Mining and Environment, 13 (2): 325–340.

[9]. Ongarbayev, I. and Madani, N. (2022). Anisotropic Inverse Distance Weighting Method: an Innovative Technique for Resource Modeling of Vein-type Deposits. Journal of Mining and Environment, 13 (4): 957–972.

[10]. Afeni, T.B., Lawal, A.I. and Adeyemi, R.A. (2020). Re-examination of Itakpe iron ore deposit for reserve estimation using geo-statistics and artificial neural network techniques. Arabian Journal of Geosciences, 13 (657).

[11]. Afeni, T.B., Akeju, V.O. and Aladejare, A.E. (2021). A comparative study of geometric and geo-statistical methods for qualitative reserve estimation of limestone deposit. Geoscience Frontiers, 12 (1): 243–253.

[12]. Zhang, J. and Yao, N. (2008). The geo-statistical framework for spatial prediction. Geo-spatial Information Science, 11(3): 180–185.

[13] Yasrebi, J., Saffari, M., Fathi, H., Karimian, N., Moazallahi, M. and Gazni, R. (2009). Evaluation and comparison of ordinary kriging and inverse distance weighting methods for prediction of spatial variability of some soil chemical parameters. Research Journal of Biological Sciences, 4 (1): 93–102.

[14]. Badel, M., Angorani, S. and Panahi, M.S. (2011). The application of median indicator kriging and neural network in modeling mixed population in an iron ore deposit. Computers & Geosciences, 37 (4): 530–540.

[15]. Kis, I.M. (2016). Comparison of Ordinary and Universal Kriging interpolation techniques on a depth variable (a case of linear spatial trend): case study of the Sandrovac Field. Rudarsko Geolosko Naftni Zbornik, 31 (2): 41–58.

[16]. Tercan, A.E. and Karayigit, A.I. (2001). Estimation of lignite reserve in the Kalburcayiri field, Kangal basin, Sivas, Turkey. International Journal of Coal Geology, 47 (2): 91–100.

[17]. Misra, D., Samanta, B., Dutta, S. and Bandopadhyay, S. (2007). Evaluation of artificial neural networks and kriging for the prediction of arsenic in Alaskan bedrock-derived stream sediments using gold concentration data. International Journal of Mining, Reclamation and Environment, 21 (4): 282–294.

[18]. Heriawan, M. N. and Koike, K. (2008). Identifying spatial heterogeneity of coal resource quality in a multilayer coal deposit by multivariate geo-statistics. International Journal of Coal Geology, 73 (3–4): 307–330.

[19]. Heriawan, M.N. and Koike, K. (2008). Uncertainty assessment of coal tonnage by spatial modeling of seam distribution and coal quality. International Journal of Coal Geology, 76 (3): 217–226.

[20]. Tahmasebi, P. and Hezarkhani, A. (2010). Comparison of optimized neural network with fuzzy logic for ore grade estimation. Australian Journal of Basic and Applied Sciences, 4 (5): 764–772.

[21]. Olea, R.A., Luppens, J.A. and Tewalt, S.J. (2011). Methodology for quantifying uncertainty in coal assessments with an application to a Texas lignite deposit. International Journal of Coal Geology, 85 (1): 78–90.

[22]. Shahbeik, S., Afzal, P., Moarefvand, P. and Qumarsy, M. (2014). Comparison between ordinary kriging (OK) and inverse distance weighted (IDW) based on estimation error. case study: Dardevey iron ore deposit, NE Iran. Arabian Journal of Geosciences, 7 (9): 3693–3704.

[23]. Thakur, M., Samanta, B., and Chakravarty, D. (2014). Support and Information Effect Modeling for Recoverable Reserve Estimation of a Beach Sand Deposit in India. Natural Resources Research, 23 (2): 231–245.

[24]. Daya, A.A. and Bejari, H. (2015). A comparative

study between simple kriging and ordinary kriging for estimating and modeling the Cu concentration in Chehlkureh deposit, SE Iran. Arabian Journal of Geosciences, 8 (8): 6003–6020.

[25]. Daya, A.A. (2015). Ordinary kriging for the estimation of vein type copper deposit: A case study of the Chelkureh, Iran. Journal of Mining and Metallurgy A: Mining, 51 (1): 1–14.

[26]. Thakur, M., Samanta, B. and Chakravarty, D. (2016). A non-stationary spatial approach to disjunctive kriging in reserve estimation. Spatial Statistics, 17, 131–160.

[27]. Jafrasteh, B., Fathianpour, N. and Suárez, A. (2018). Comparison of machine learning methods for copper ore grade estimation. Computational Geosciences, 22 (5): 1371–1388.

[28]. Rahimi, H., Asghari, O. and Afshar, A. (2018). A geo-statistical investigation of 3D magnetic inversion results using multi-Gaussian kriging and sequential Gaussian co-simulation. Journal of Applied Geophysics, 154, 136–149.

[29]. Rezaei, A., Hassani, H., Moarefvand, P. and Golmohammadi, A. (2019). Grade 3D Block Modeling and Reserve Estimation of the C-North Iron Skarn Ore Deposit, Sangan, NE Iran. Global Journal of Earth Science and Engineering, 6, 23–37.

[30]. Arinze, I.J., Emedo, C.O. and nad Ugbor, C.C. (2019). A scalar-geometric approach for the probable estimation of the reserve of some Pb-Zn deposits in Ameri, southeastern Nigeria. Journal of Sustainable Mining, 18 (4): 208–225.

[31]. Zerzour, O., Gadri, L., Hadji, R., Mebrouk, F. and Hamed, Y. (2020). Semi-variograms and kriging techniques in iron ore reserve categorization: application at Jebel Wenza deposit. Arabian Journal of Geosciences, 13 (16): 1–10.

[32]. Uyan, M. and Dursun, A.E. (2021). Determination and modeling of lignite reserve using geostatistical analysis and GIS. Arabian Journal of Geosciences, 14 (312).

[33]. Dinda, K. and Samanta, B. (2021). Non-Gaussian Copula Simulation for Estimation of Recoverable Reserve in an Indian Copper Deposit. Natural Resources Research, 30 (1): 57–76.

[34]. Madani, N., Maleki, M. and Soltani-Mohammadi, S. (2022). Geo-statistical modeling of heterogeneous geo-clusters in a copper deposit integrated with multinomial logistic regression: An exercise on resource estimation. Ore Geology Reviews, 150 (3–4): 105132.

[35]. Pebesma, E.J. (2004). Multivariable geo-statistics in S: the gstat package. Computers & Geosciences, 30 (7): 683–691.

[36]. Seyed Mousavi, S.Z., Tavakoli, H., Moarefvand, P. and Rezaei, M. (2020). Micro-structural, petro-graphical and mechanical studies of schist rocks under the freezing-thawing cycles. Cold Regions Science and Technology, 174, 103039.

[37]. Seyed Mousavi, S.Z. and Rezaei, M. (2022). Correlation assessment between degradation ratios of UCS and non-destructive properties of rock under freezing-thawing cycles. Geoderma, 428, 116209.

یک روش ترکیبی زمین‌آماری برای تخمین بهینه منبع معدن زیرزمینی انگوران

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چکیده:

تخمین منبع و تعیین توزیع عیار یکی از مهم‌ترین مراحل در برنامه‌ریزی و طراحی معادن روباز و زیرزمینی اســت. در این تحقیق، از یک روش جدید بر مبنای ترکیب بهینه روش‌های کریجینگ شاخص (IK)، کریجینگ ساده (SK) و وزن‌دهی عکس فاصله (IDW) برای تخمین منبع معدن زیرزمینی انگوران استفاده شده است. بدین منظور، ابتدا بلوک‌های باطله با استفاده از روش IK از مدل بلوکی حذف گردید. سپس، مقدار منبع معدنی با استفاده از روش‌های SK و IDW تخمین زده شد. در هر سه روش مورد استفاده، واریوگرام‌هایی برای تعیین عیار کانی روی توسعه داده شد. تجزیه و تحلیل واریوگرام‌ها در سه جهت مختلف نشان داد که منبع مورد مطالعه آنیزوترپ است. همچنین، نتایج اعتبارسنجی اثبات کرد که ضریب همبستگی بین مقادیر واقعی و مقادیر تخمینی کانه روی توسط روش‌های SK و IDW به ترتیب برابر با 0/76 و 0/75 می‌باشد. با در نظر گرفتن این نتیجه رضایت‌بخش، مدل سه بعدی منبع با استفاده از روش IK تهیه شد که در آن، بخش‌های کانه و باطله معدن زیرزمینی انگوران به صـورت جداگانه تعیین گردید. با توجه به روش فوق، مقدار منبع محاســبه شــده در معدن زیرزمینی انگوران با استفاده از روش SK برابر با 1373962/5 تن با عیار متوسط 31/11% و با استفاد از روش IDW برابرا با 1349325 تن با عیار متوسط 31/88% بدست آمد. نتایج اعتبارسنجی نشان داد که روش پیشنهادی بر اساس ترکیب بهینه روش‌های IK، SK و IDW می‌توان به صورت موفقیت آمیزی برای مدل‌سازی منبع و تخمین عیار معدن زیرزمینی انگوران مورد استفاده قرار گیرد.

کلمات کلیدی: معدن زیرزمینی انگوران، تخمین منبع، کریجینگ شاخص، کریجینگ ساده، وزن‌دهی عکس فاصله.