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Block model optimization and resource estimation of the Angouran Mine by transferring the exploratory data from the local coordinate system to the UTM

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Original scientific paper

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Abstract

Resource estimation is one of the most important steps in the mining process. Precise resource estimation has a significant influence on the optimization of subsequent mining steps, i.e. mine planning and scheduling. The previous resource estimation in the Angouran Mine was conducted based on the provided information in the local coordinate system which causes considerable errors in estimations. Therefore, an attempt is made in this research to optimize the block model of the Angouran Mine and resource estimation based on the information in the UTM global coordinate system. For this purpose, exploratory data is firstly transferred from the local coordinate system to the UTM environment. Then, block model optimization is conducted using indicator kriging (IK) in which the waste blocks are removed and the block model was optimized. Finally, resource estimation is performed using the inverse distance weighting (IDW) and simple kriging (SK) methods. After variogram analyses in different directions, it was found that the mine deposit is anisotropic. Also, validation results showed that the acquired correlation coefficient in the carbonate and sulfide sections for IDW, SK and IK is 0.86, 0.87 and 0.92, and 0.88, 0.87 and 0.92, respectively. Finally, the obtained grades and tonnages are compared with the actual data of the exploratory boreholes, mined blocks and previous resource estimation in the mine. Comparative results showed that the obtained grades and tonnages from both previous and new models are over-estimated and higher than the actual values. The minimum errors of grade estimation equal 46% and 23.1% for previous and new resource estimations (before and after the waste removal), respectively. Also, the mining errors of tonnage estimation are 50.29% and 28.37% for previous and new models, respectively. This field comparison proved that transferring the exploratory data to the UTM system, utilization of the IK to remove the waste blocks and applying the SK for resource estimation lead to the optimization of the block model and a reduction in the estimation error compared to the previous estimations for the mine.

Keywords:
resource estimation; utm; indicator kriging; simple kriging; inverse distance weighting

1. Introduction

The process of resource estimation plays an essential role in the planning and scheduling of mining projects and the future designs of a mine. Modeling the spatial changes of grade in a deposit leads to a more accurate estimation of the deposit main characteristics, such as tonnage, metal content and average grade (**Battalgazy and Madani, 2019**). Hence, the final feasibility study of a deposit is extensively affected by the accuracy of the resource estimation. Actually, an accurate resource estimation can help the resource owners to make a precise decision to invest or not to invest. To do this, selecting a suitable estimation method for accurate resource estimation is very crucial which is well-matched with the deposit characteristics, i.e. geological, structural, and geo-

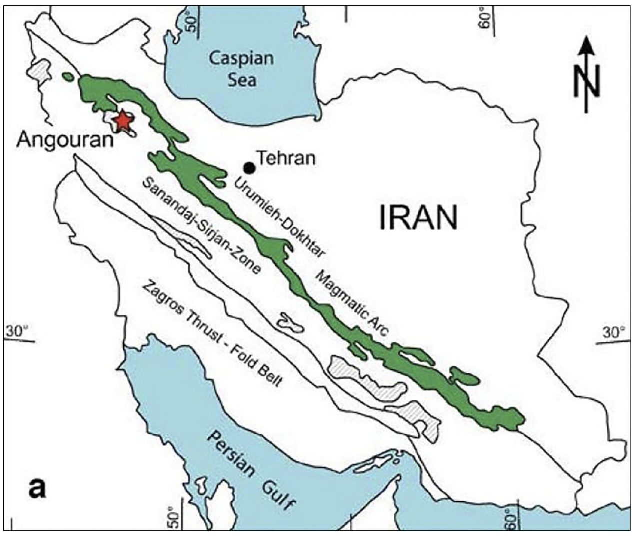

Figure 1: Location of the Angouran Mine on the structural map of Iran (**Seyed Mousavi et al., 2020b**)

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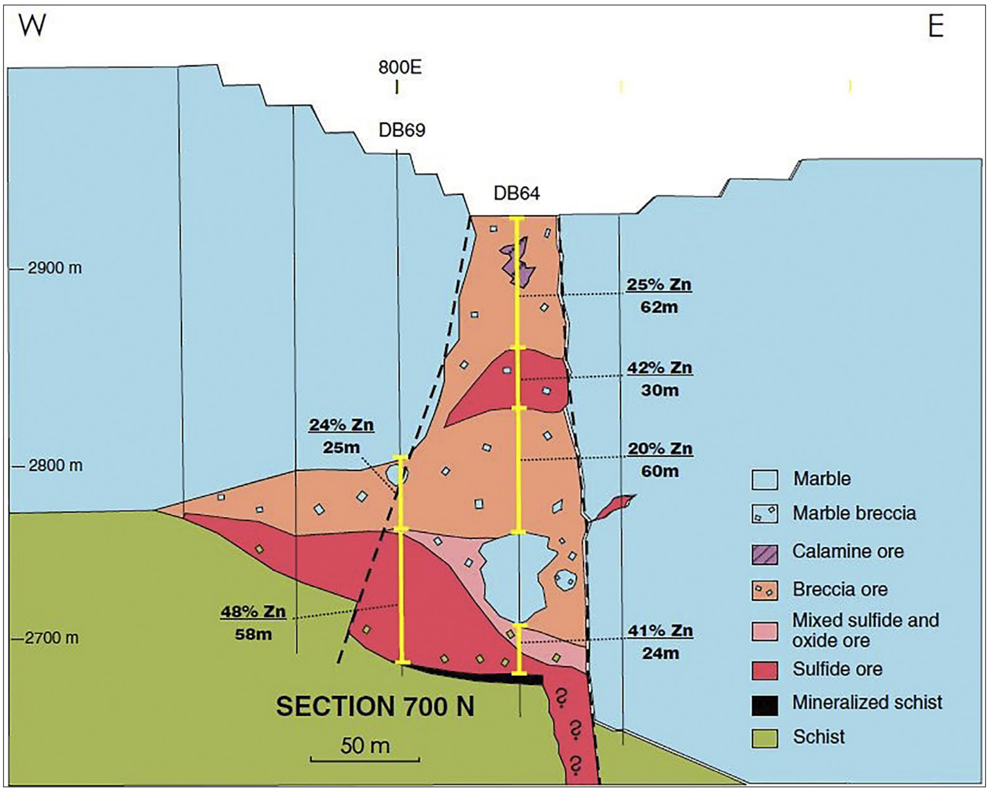

Figure 2: East-west geological section of the Angouran Mine deposit (**Seyed Mousavi et al., 2020c**)

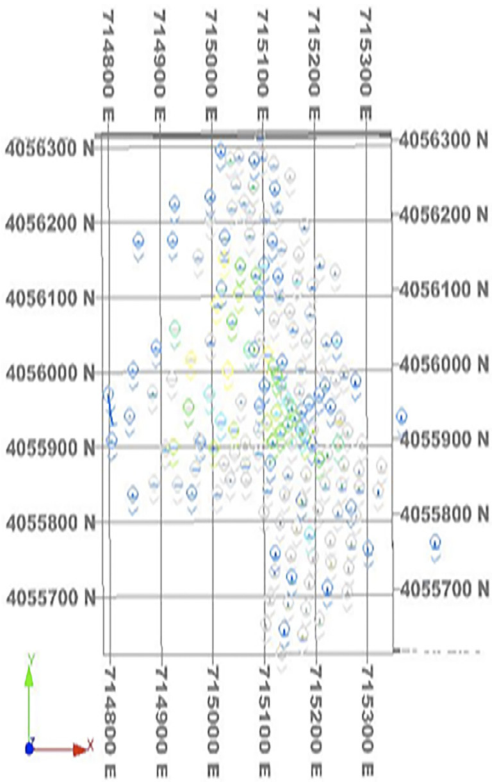

Figure 3: A view of the location of the drilling network in the UTM environment

metrical properties. Since utilizing an unsuitable approach for resource estimation leads to about a ±50% inaccuracy, choosing an applied suitable technique for resource estimation is the main worry of mine evaluators. Thus, it can definitely be claimed that the mining upcoming efficiency is strongly correlated with the results of resource estimation in terms of quantity and quality, i.e. tonnage and grade (**Dominy et al., 2002; Kerbati et al., 2020; Zerzour et al., 2021**).

Different approaches including conventional, geostatistical, and artificial intelligence techniques have been used for resource estimation up to now (**Afeni et al.,**

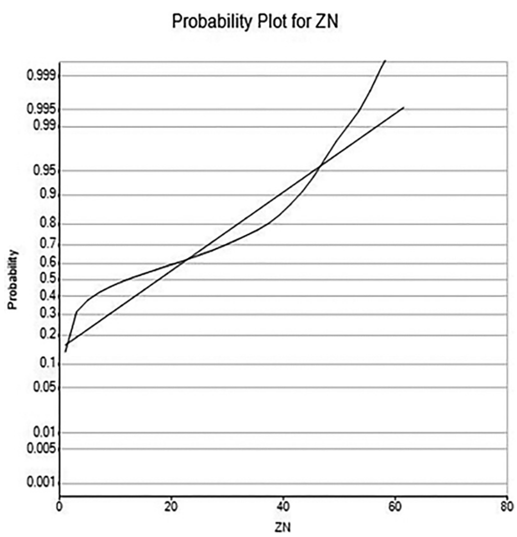

Figure 4: Cumulative element distribution diagram of the database

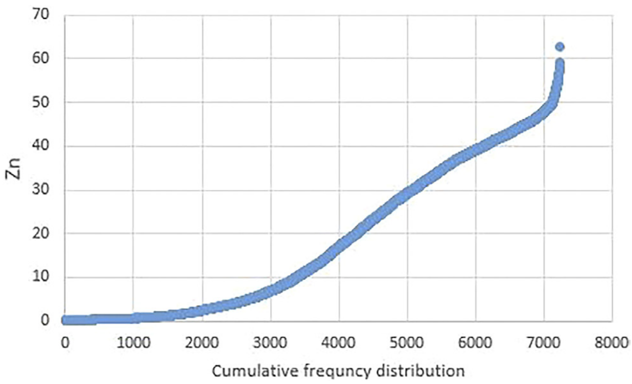

Figure 5: Cumulative frequency distribution of the zinc grade deposit

2020). In conventional techniques (i.e. cross-section approaches), random distribution is supposed and the sample values are independent from each other. The most common ability of these techniques is that the total estimation of a resource can be provided. Nevertheless, they can't be capable in defining the values of mineralization conjunction between a deterministic and indeterminist points. Hence, the conventional techniques are often involved with an over-estimation of inherently un-economic resources and an under-estimation of possible economic resources (**Zhang and Yao, 2008; Afeni et al., 2021**). However, in the geostatistical techniques, samples in a deposit are spatially correlated together unlike the conventional approaches. Resource estimation

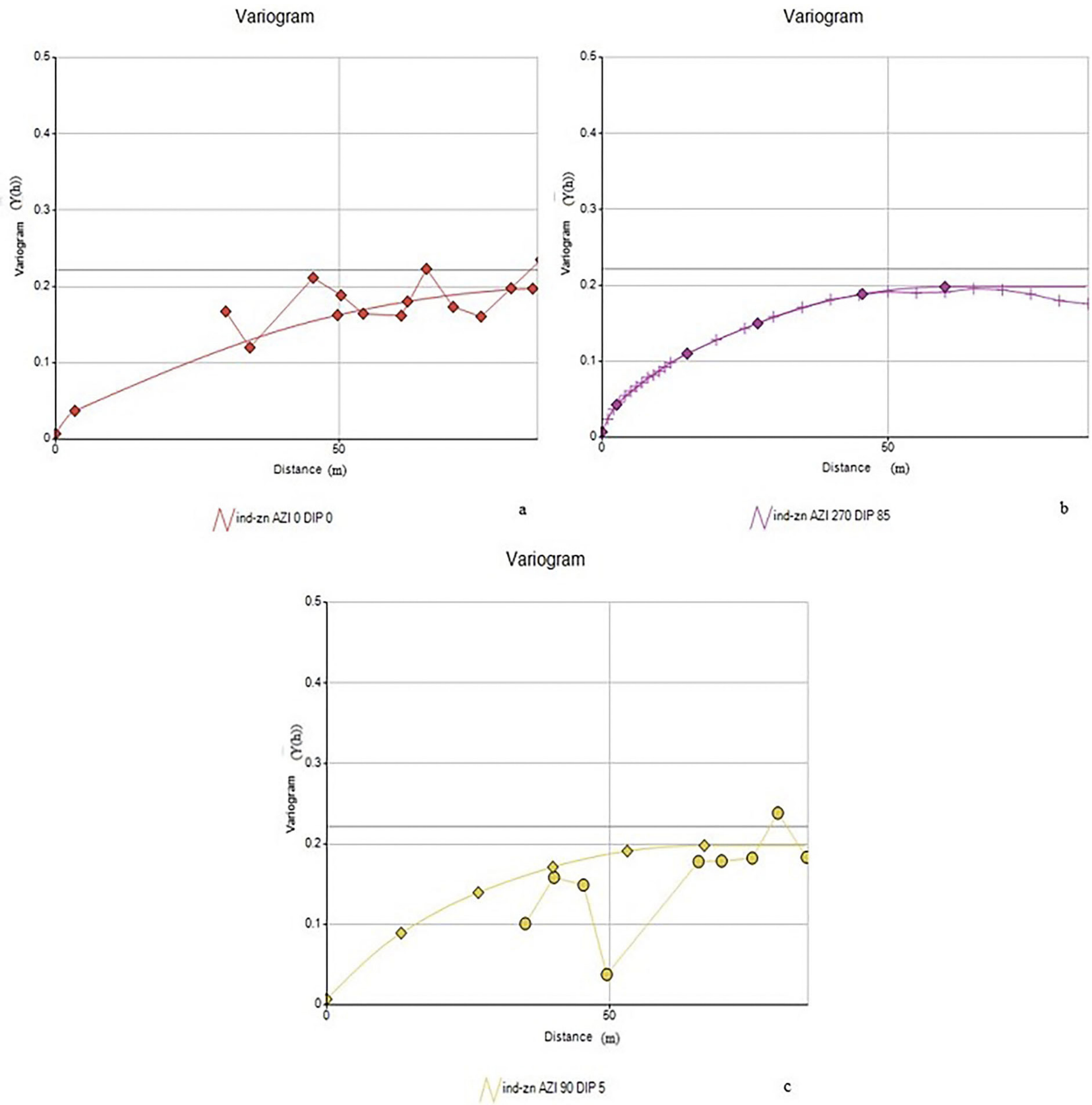

Figure 6: IK variograms in the carbonate section: a) Z-direction with -90° rotation angle, azimuth 0° and inclination 0°, b) Y-direction with rotation angle 0°, azimuth 270° and inclination 85°, c) X-direction with rotation angle 85°, azimuth 90° and slope 5°

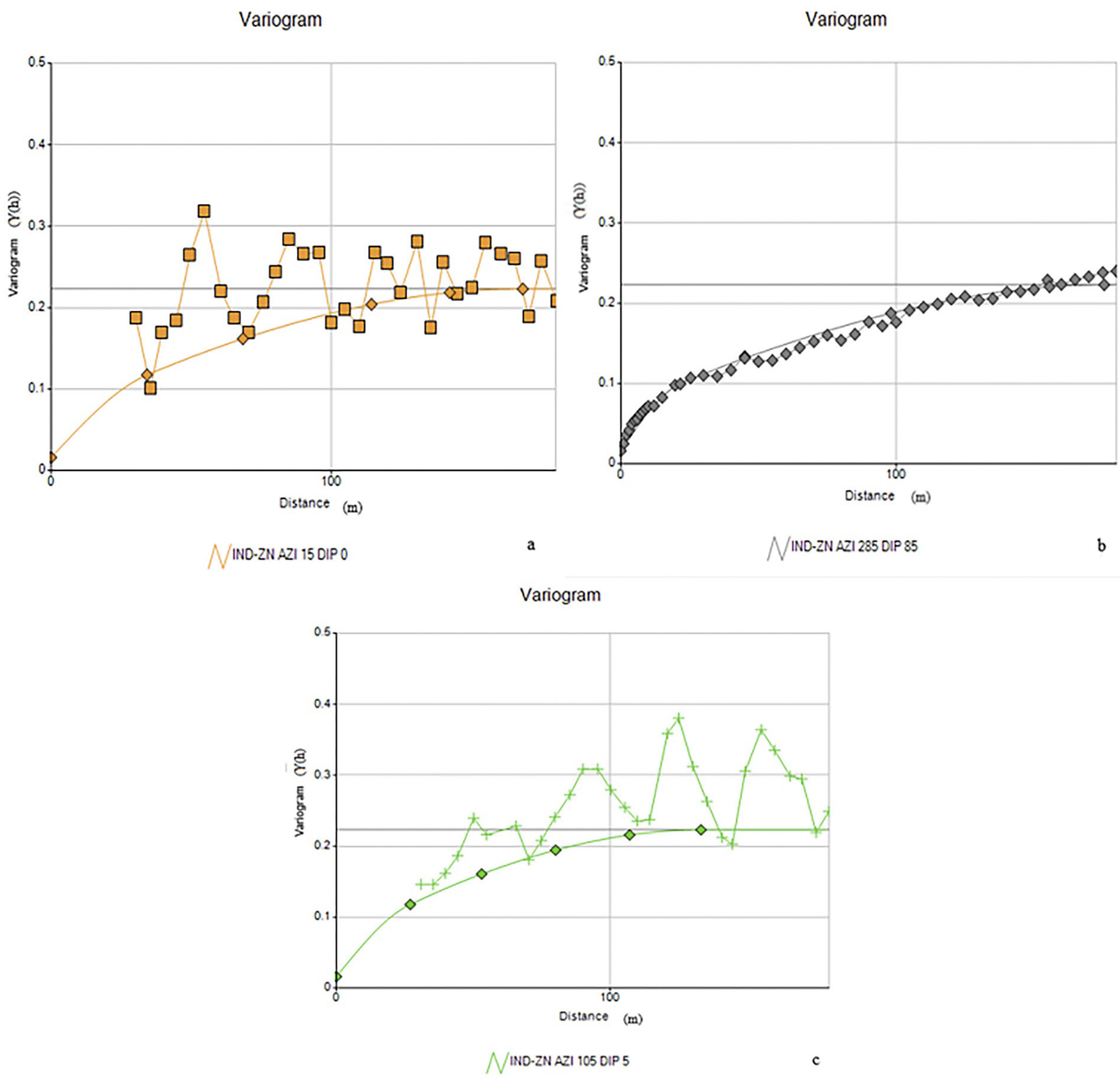

Figure 7: IK variograms in the sulfide section: a) Z-direction with rotation angle -75°, azimuth 15° and slope 0°, b) Y-direction with rotation angle 0°, azimuth 285° and slope 85°, c) X-direction with rotation angle 85°, azimuth 105° and slope 5°

in the geostatistical techniques is conducted based on the variography analysis and kriging evaluation. In variography analysis, the amount of possible interdependencies between the identified values of a deposit is determined using an analytical equation. In fact, geostatistical techniques have become the main approaches applied to estimate the grade and tonnage of deposits. Kriging techniques including ordinary kriging, universal kriging, indicator kriging and cokriging are the worldwide utilized resource estimation tools in the geostatistical modeling. Kriging is a variant of the basic linear regression techniques allowing the estimation of a single regionalized variable in un-sampled location. In these techniques, the optimum weights are assigned for minimizing the estimation errors. Geostatistical techniques were efficiently utilized for ore resource estimation by different research studies (**Yasrebi et al., 2009; Badel et al., 2011; Kis, 2016; Kasmaee et al., 2018**).

Badel et al. (2011) used the median indicator kriging and neural network techniques for an iron ore estimation and acquired acceptable results. A variance-based technique was used by **Tercan and Karayigit (2001)** to estimate a lignite deposit. Neural network and geostatistical approaches were applied by **Misra et al. (2007)** to evaluate an arsenic resource and confirmed the superiorities of the geostatistical technique compared to the neural network model. Considering the geometrical and chemical characteristics of a coal seam, **Heriawan and Koike (2008)** estimated the resource quality and quantity by several suitable geostatistical methods. **Tahmasebi & Hezarkhani (2010)** applied some intelligent techniques for resource estimates and proved the superi-

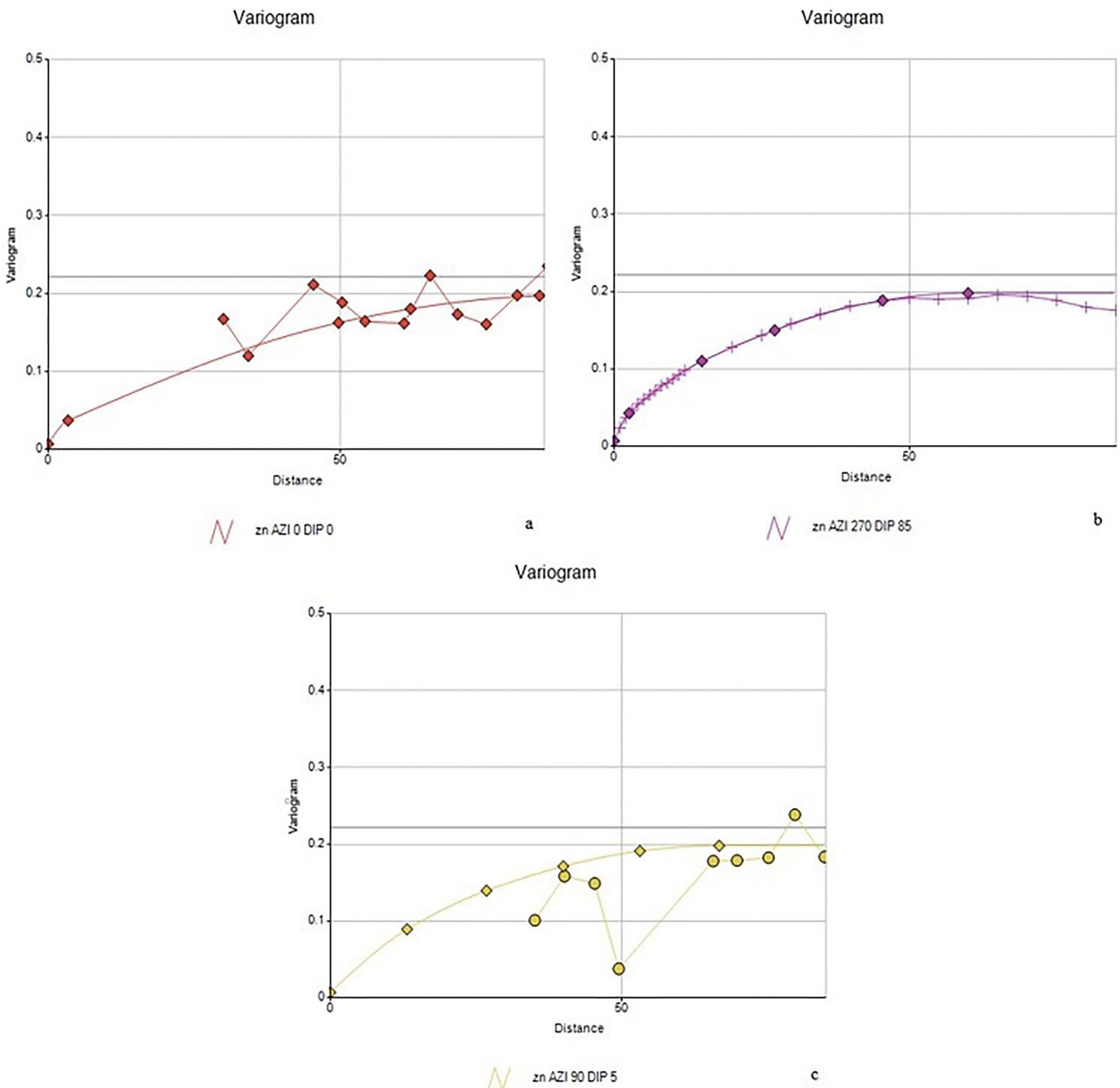

Figure 8: IDW variograms in the carbonate section: a) Z-direction with -90° rotation angle, azimuth 0° and inclination 0°, b) Y-direction with rotation angle 0°, azimuth 270° and inclination 85°, c) X-direction with rotation angle 85°, azimuth 90° and slope 5°

ority of the genetic algorithm compared to the others. **Olea et al. (2011)** used some geostatistical techniques to estimate the uncertainty in determining the coal tonnage in a lignite deposit. **Rao et al. (2014)** applied a kriging method to successfully estimate the grade of an iron reserve. Ordinary kriging and inverse distance weighting techniques used for iron reserve estimation by **Shahbeik et al. (2014)** confirmed the superiorities of ordinary kriging compared to the inverse distance weighting technique. **Sadeghi et al. (2015)** utilized the integration of geostatistical and fractal models for iron deposit estimation. Comparative analysis between simple and ordinary kriging methods in a copper resource estimation proved the superiority of ordinary kriging (**Daya, 2015; Daya et al., 2015**). A combination of spatial and the kriging techniques applied by **Thakur et al. (2016)** for resource estimation and proved their accuracies. **Silva and Almeida (2017)** presented a combination of geostatistical techniques for reserve estimation by providing the improved stochastic geological model. **Rahimi et al. (2018)** used the geostatistical modeling of three dimensional magnetic inversion results using multi-Gaussian kriging and sequential Gaussian co-simulation. **Marwanza et al. (2018)** conducted kriging modeling to estimate a copper deposit efficiently. Geostatistical and neural network approaches used by **Jafrasteh et al. (2018)** for copper grade estimation in which the superiority of geostatistical method was proven. **Behera et al. (2019)** performed geostatistical modeling combined with geological modeling for the estimation of an iron bauxite deposit. They concluded that this combined method is an objective tool for geostatic description, the presentation

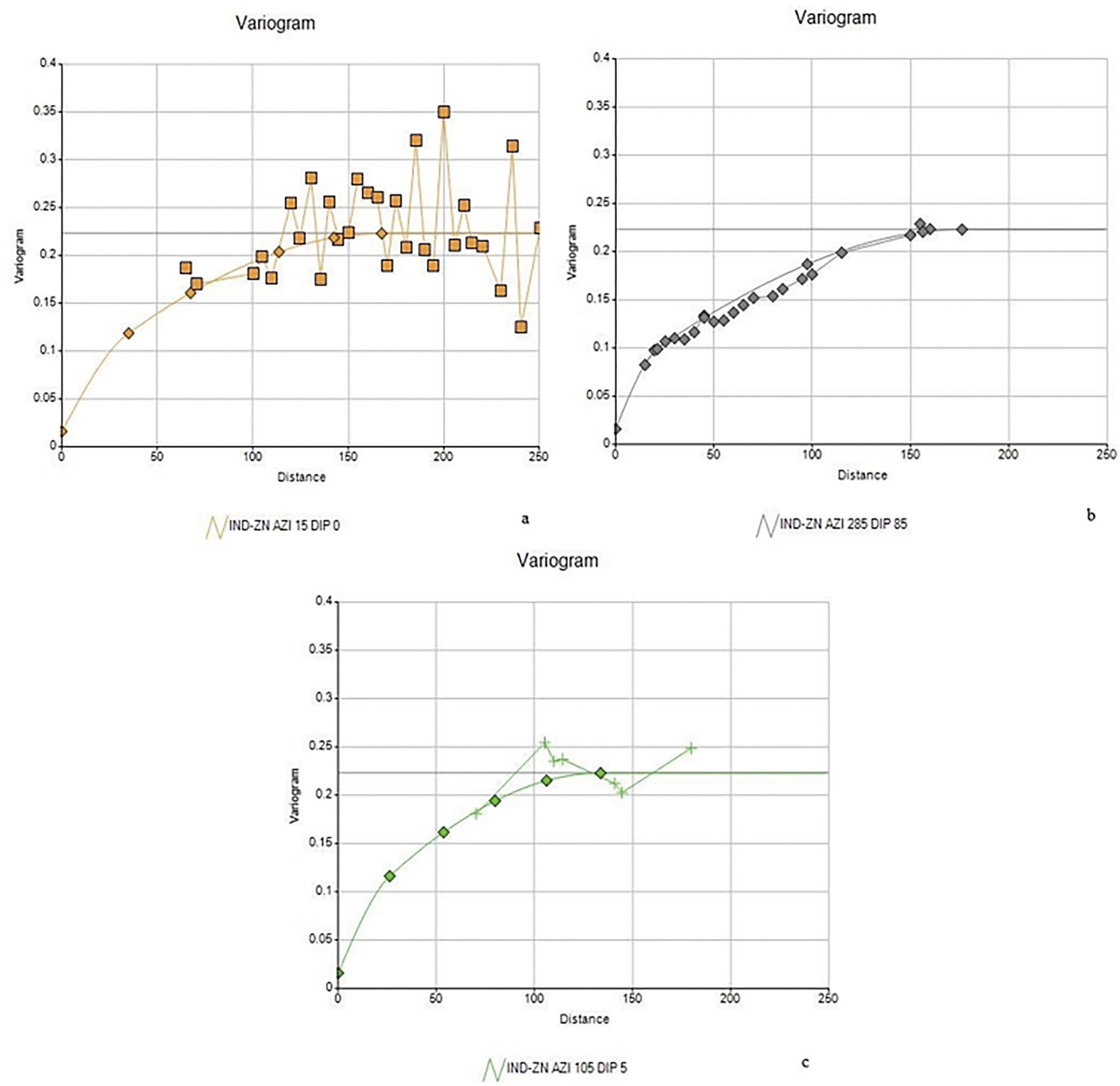

Figure 9: IDW variograms in the carbonate section: a) Z-direction with rotation angle -75°, azimuth 15° and inclination 0°, b) Y-direction with rotation angle 0°, azimuth 285° and inclination 85°, c) X-direction with rotation angle 85°, azimuth 105° and slope of 5°

of mineral boundaries, the estimation of mineral content with the associated uncertainty assessment and the presentation of grade-tonnage relationships. Resource estimation of an iron resource was conducted by **Rezaei et al. (2019)** using 3D grade simulation. They found that the proposed 3D model can simplify the available complexity in resource estimation. The suitability of a geometrical technique confirmed by **Arinze et al. (2019)** to estimate a zinc-lead resource. A successful application of Geostatistical simulation proved by **Zerzour et al. (2020)** for the estimation of a complex iron resource. **Uyan and Dursun (2021)** confirmed a suitability of geostatistical and GPS modeling to estimate a lignite resource. The higher accuracy of simulation-based techniques compared to the geostatistical methods was proven by **Dinda and Samanta (2021)** in the copper resource estimation. Geostatistical and regression-based techniques were applied by **Madani et al. (2022)** for copper deposit evaluation and proved that these techniques are capable in covering the involved heterogeneity in resource estimation.

Due to the presence of 50% error in the previous resource estimation of the Angouran Mine, block model optimization and re-estimation of the mine resource are investigated in this study. For this purpose, the exploration drilling database is firstly transferred from the local coordinate system to the UTM. After that, block model optimization is implemented by the IK method and the waste blocks are removed. Lastly, IDW and SK techniques are used for resource estimation.

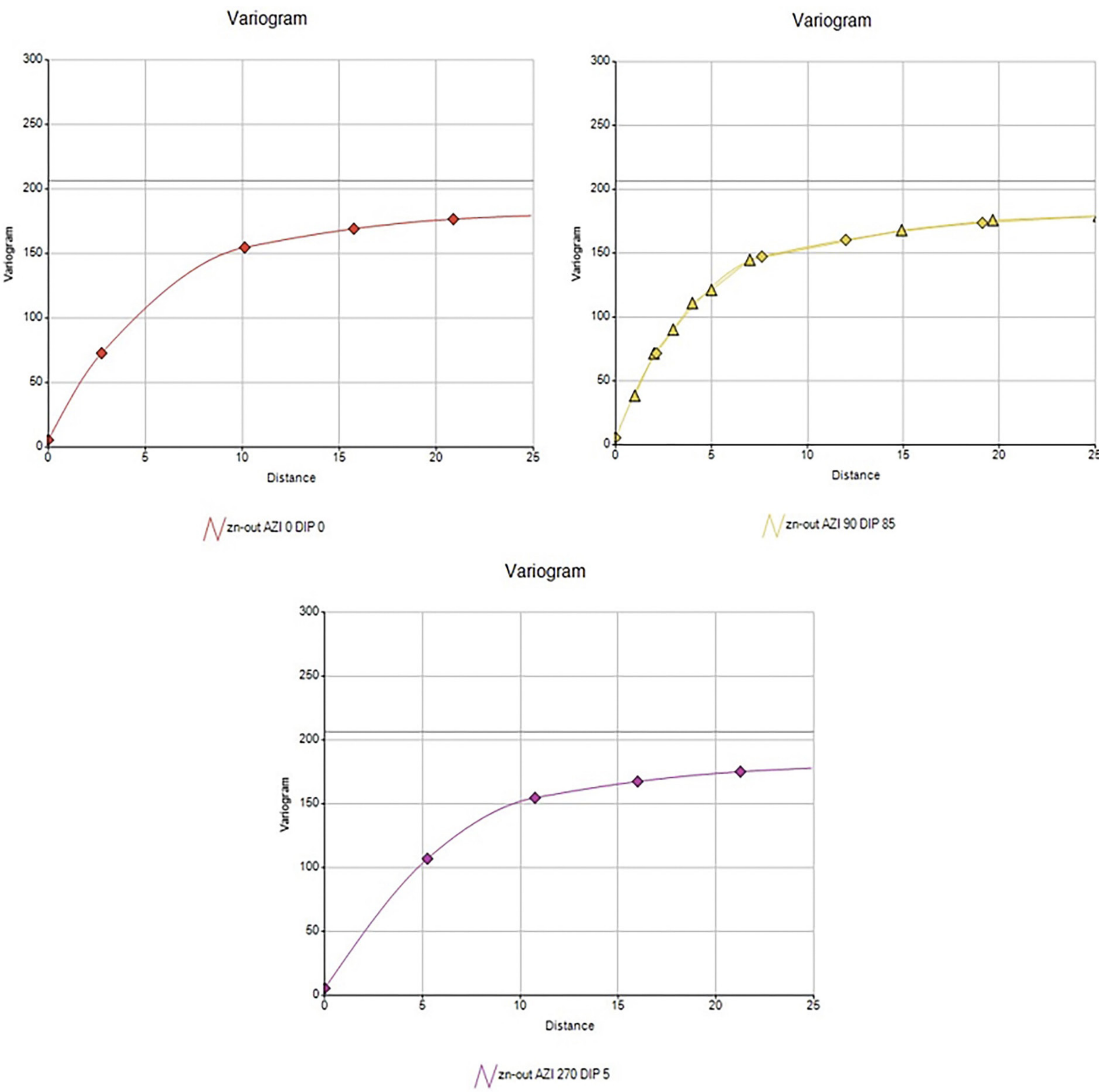

Figure 10: SK variograms in the carbonate section: a) Z-direction with rotation angle -90°, azimuth 0° and inclination 0°, b) Y-direction with angle rotation 0°, azimuth 90° and inclination 85°, (c) X-direction with rotation angle 95°, azimuth 270° and slope 5°

2. Angouran Mine

Angouran Mine is located 135 km south-west of Zanjan and 450 km north-west of Tehran. This mine is positioned in a mountainous area with an average altitude of 2950 meters above sea level. The geographical coordinates of the mine are 40-36′ longitude and 20-47′ latitude. Angouran Mine is one of the main lead and zinc mines in the world. From the geological viewpoint, Angouran Mine is situated in the Sanandaj-Sirjan Zone as demonstrated in **Figure 1**. This area is at the contact point of the Tertiary volcanic belt of Urmia-Dokhtar and the Sanandaj-Sirjan Zone in connection with the Zagros orogenic belt. An east-west geological section of the Angouran Mine deposit is shown in **Figure 2**. The mine ore deposit is positioned between the limestone and schist layers as hanging and foot walls, respectively. Most of its rock floors are made of metamorphic limestone. In this area, by passing the carbonate section to the west and to the metabasic rocks, the effects of folding system are reduced. The deposit is located at the central part or the anticline core. The host rock of the Angouran deposit is situated in metamorphic complex from the Neoproterozoic to the Cambrian and Lower Miocene. It was deformed by extensional processes in the area and formed a collection of amphibolite, serpentinite, gneiss, mica-schist and calcite, and crystalline limestone (marble) as can be seen in **Figure 2**. The mentioned marble rocks are available in some areas as an interlayer with amphibolite, gneiss and micaschist, which in some places have a thick-

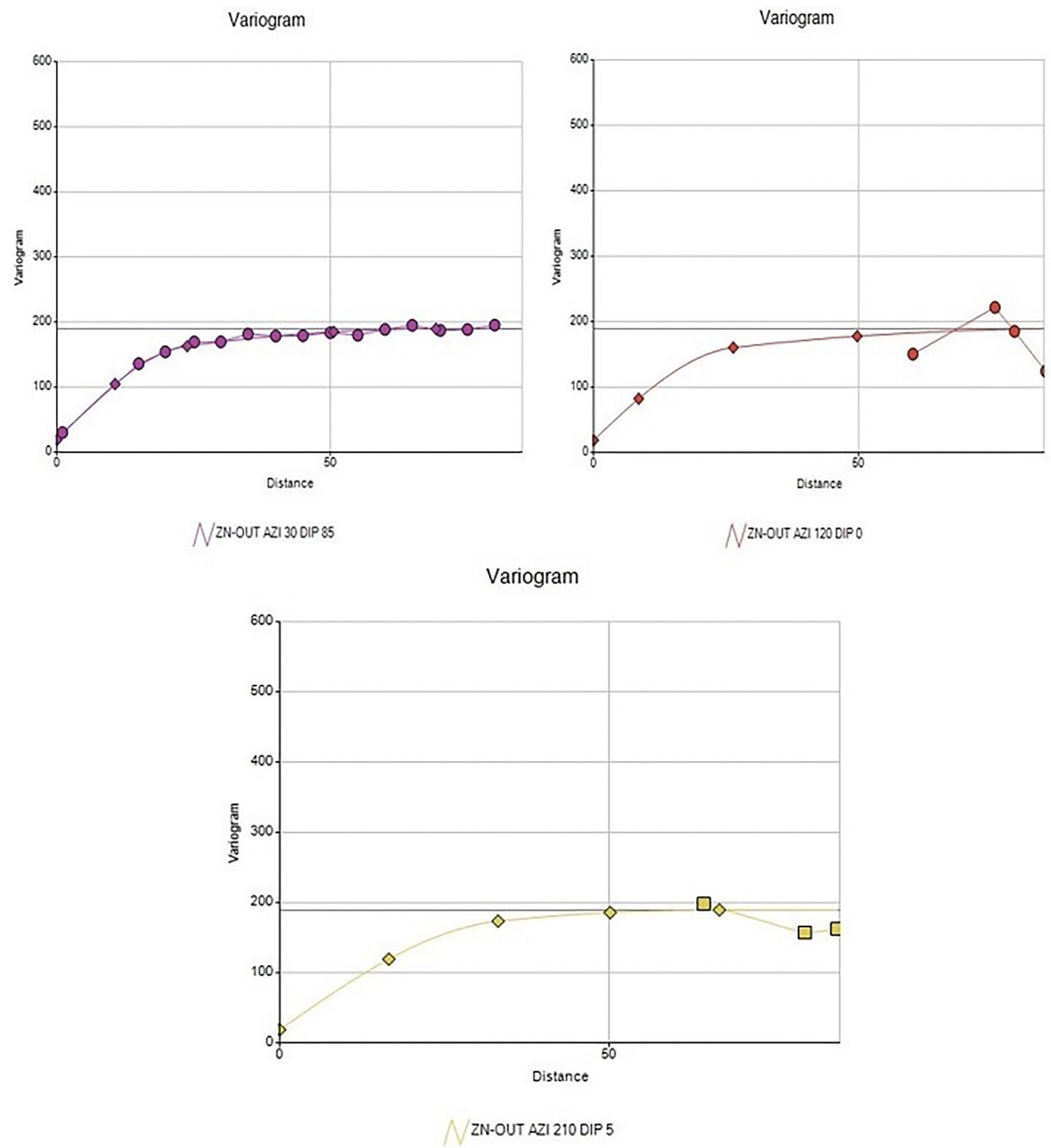

Figure 11: SK variograms in the sulfide section (a) Z-direction with rotation angle 30°, azimuth 120° and inclination 0°, b) Y-direction with rotation angle 0°, azimuth 30° and inclination 85°, c) X-direction with rotation angle 85°, azimuth 210° and slope 5°

Table 1: Variograms characteristics related to three used methods in the carbonate section

Variogram type	Range (m)	Sill (%)	Nugget effect	Rotate direction (°)	Direction	Method
Spherical	53.3	0.198	0.007	-90	Z	IK
	45.5			0	Y	
	84.1			85	X	
Spherical	54.3	0.198	0.007	-90	Z	IDW
	45.5			0	Y	
	54.3			85	X	
Spherical	31.2	176.83	5.548	-90	Z	SK
	30.2			0	Y	
	28.3			95	X	

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Table 2: Variograms characteristics related to three used methods in the sulfide section

Variogram type	Range (m)	Sill (%)	Nugget effect	Rotate direction (°)	Direction	Method
Spherical	106.7	0.223	0.016	-90	Z	IK
	155.8			0	Y	
	142.0			85	X	
Spherical	106.7	0.223	0.016	-90	Z	IDW
	155.8			0	Y	
	142.0			85	X	
Spherical	66.7	189.60	18.96	30	Z	SK
	69.2			0	Y	
	90.1			85	X	

ness of 300 m. By passing through the carbonate section to the metabasic rocks, there is weak folding. The existing faults in the Angouran Mine area are divided into two categories of main faults and sub-faults. The main faults have EW and NW-SE extension with a longitudinal extension of more than 200 m, while the sub-faults have a longitudinal extension of less than 50 m. It should be noted that the most changes in geological sections occurred by major faults with EW extension (**Seyed Mousavi et al., 2019, 2020a; Seyed Mousavi and Rezaei, 2022; Rezaei and Ghasemi, 2023**).

2.1. Statistical analysis database

Block modeling and resource estimation using modeling software involved three specific steps. These steps are creating the geometrical model of deposit, constructing the resource estimation model, and combining the geometrical model and resource estimation in order to evaluate the reserve quality and quantity. For accurate reserve estimation using the software modeling, precise information, such as topography of the resource surface, location of the ore deposit, characteristics of the exploratory boreholes, grade of main and companion minerals, mapping points, and geological condition is needed. In fact, this information directly affects the resource estimation results. This information is classified and used to perform the resource estimation process.

In this research, a database comprising 179 boreholes with a total length of 22899.41 m are provided. In this database, 6413.47 m of provided cores have a higher grade than 3% and 81.6782 m have a lower grade than 3%. Also, 13.9633 m of cores are missed and there is no information about them. For optimization objectives, exploration data has been transferred to the UTM coordinate system as shown in **Figure 3**. Statistical examination of the database, recognition of the statistical characteristics of the raw data population, and especially the nature of their distribution function can help to perform accurate resource estimation. Statistical analyses of single community and multi-community as well as out-of-order values of the database are checked and shown in **Figures 4** to **5**. As can be seen in **Figure 4**, the cumulative data graph is deviated from a straight line, which shows the multi-communities of the database. Therefore, the grades lower and higher than 3% are considered as separate communities. The grades lower than 3% are in the schist and limestone and aren't checked further, but the higher grades than 3% should be checked. Also, according to **Figure 5**, the data with grades higher than 56.92% which are outlier and far from the other data are considered as the out-of-line data and replaced by 56.92. Then, according to the existing faults and boreholes information, the block model is made in carbonate and sulfide parts. In each part, the distance is estimated by the IDW method. After that, the block model is estimated by the IK method and accordingly, the waste blocks are removed to optimize the estimation space. Finally, the index block model is estimated twice by the IDW and SK methods. The resource estimation is also done and the obtained results are compared with the actual extraction steps. Before all the above steps, the boreholes database is transferred from the local coordinate system to the UTM coordinate system, as previously mentioned (see **Figure 3**).

3. Variogram analysis

Variograms are commonly developed to describe the spatial relationship between the deposit characteristics (i.e. grade) at different points. With the help of variograms, important characteristics of the deposit that are effective in the resource estimation are investigated. Variograms are the most frequently geostatistical tools used in mining engineering for quantitative definition of the spatial continuities of the various geological attributes such as mineralization grades, metal accumulations, and thickness of mineralized zones. The common variogram models are exponential, spherical, Gaussian, linear, and power types (**Pebesma, 2004**). From these variogram models, the spherical type is the most frequently used model in mining engineering. On the other hand, a variogram is the most suitable tool for anisotropy identifying in different directions i.e. geometrical and regional anisotropies.

For the Angouran resource, the IK variograms in the carbonate and sulfide sections are presented in **Figures 6** and **7**, respectively. Also, the IDW variograms in the carbonate and sulfide sections are demonstrated in **Figures 8** and **9**, respectively. Moreover, the variograms related to the SK method in the carbonate and sulfide sections are separately depicted in **Figures 10** and **11**, respectively. Furthermore, the variogram characteristics of all three methods in the carbonate and sulfide sections are given in **Tables 1** and **2**, respectively. According to these variogram analyses, the obtained variograms in IK and IDW have the same sill and Nugget but unlike rotation influences. Meanwhile, SK have different characteristics with IK and IDW methods. These results prove the geometrical and regional anisotropies in the database.

4. Block modeling

The block model describes the three-dimensional volume with relatively small and parallel structures. Block models are suitable tools for resource estimation, mine evaluation, and mine planning, including pit design or optimization of extraction sequences and mine planning. In most cases, mineral resource estimation is obtained using block models. The block model geometry depends on the characteristics of the reservoir, the modelled geological features, the requirements of mine planning, and the utilized equipment size and type. Determining the block size and geometry is an important decision in resource modeling. The block geometry is usually determined based on the distance of drilling data and other engineering characteristics. Larger blocks are easier to estimate than smaller blocks, meaning that the predicted values are more likely closer to the actual block values. On the other hand, a very large block size is not useful for pit optimization and mine planning. According to literature, the optimum block size is in the range of 1/2-1/3 of drilling data intervals (**Revuelta, 2018**).

According to the geological conditions and the 25 m distance of new exploration network in the Angouran

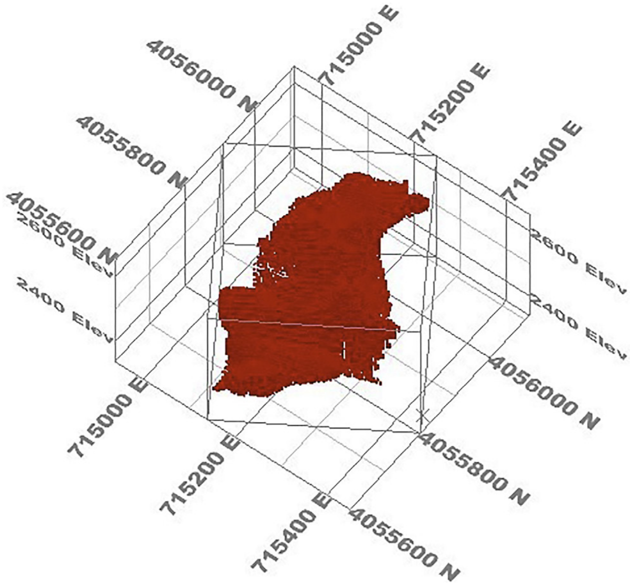

Figure 13: Angouran Mine block model in the sulfide section

Mine, ore blocks with dimensions of 10×10×10 are considered for block modeling. As it is obvious, 10 m or block dimension is in the range of 1/2-1/3 of exploratory network distance and is in accordance with the literature suggestion. **Figures 12** and **13** show the block model of the Angouran Mine in the carbonate and sulfide sections, respectively.

4.1. Block model optimization

Using the IK method, waste blocks are separated from the ore blocks and removed from the resource modeling considering the defined threshold grade. This process increases the resource estimation accuracy by itself. As there is a smoothing type in resource estimation methods in which lower grades are matched with higher grades that can cause some possible errors. To remedy this problem, removing the waste blocks is the best solution. **Figures 14**

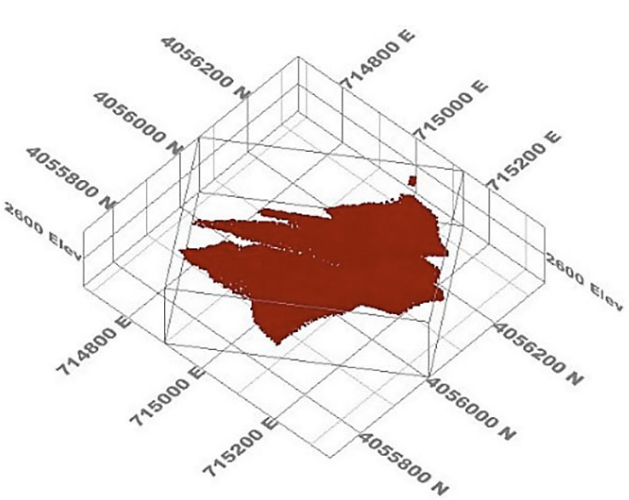

Figure 12: Angouran Mine block model in the carbonate section

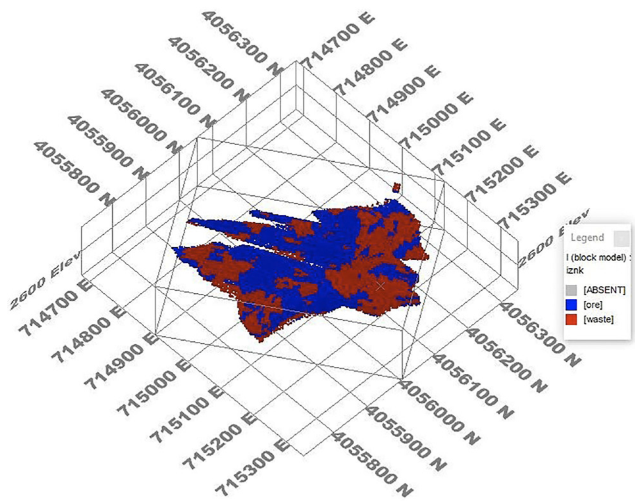

Figure 14: IK block model in the carbonate section before removing the waste blocks

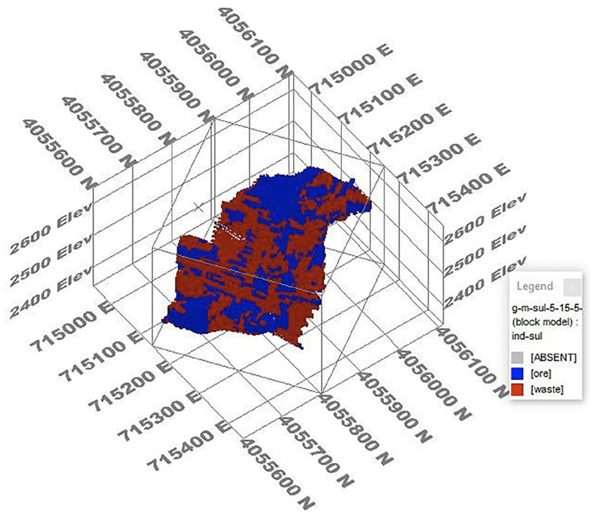

Figure 15: IK block model in the sulfide section before removing the waste blocks

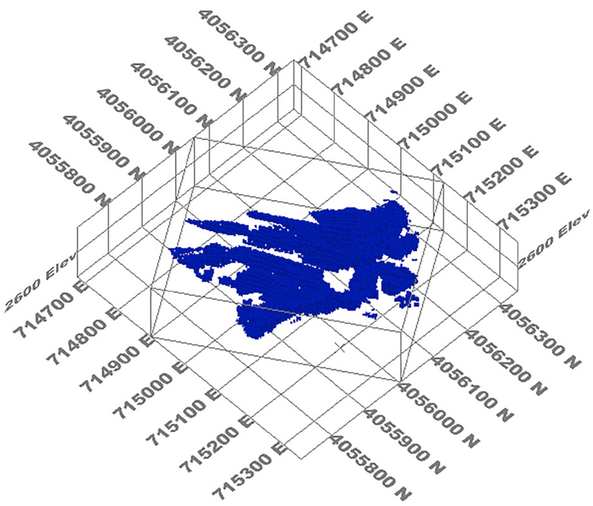

Figure 16: IK block model in the carbonate section after removing the waste blocks

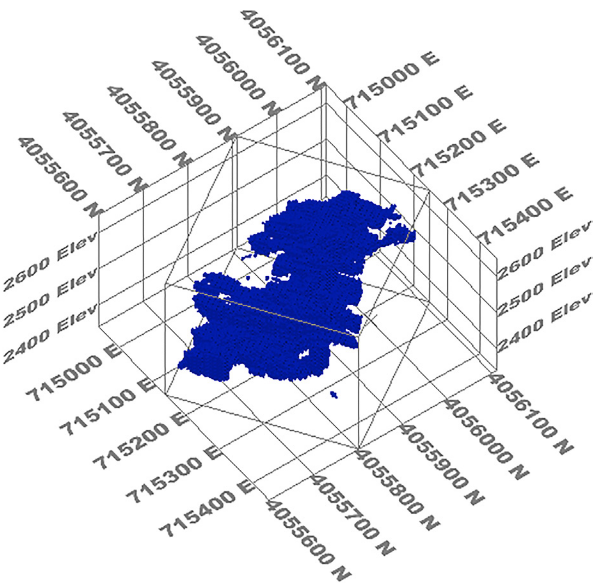

Figure 17: IK block model in the sulfide section after removing the waste blocks

and **15** show the IK block models in the carbonate and sulfide sections before removing the waste blocks, respectively. Also, IK block models in the carbonate and sulfide sections after removing the waste blocks are represented in **Figures 16** and **17**, respectively.

5. Resource estimation

According to the variogram analyses and block models, the amount of zinc ore in the deposit is estimated using the IDW and SK methods. Grade-tonnage curves are the most effective tools that help the mine designers and managers to correctly determine the long-term, medium-term and short-term parameters for ore production. The obtained tonnage-grade curves from the IDW method in carbonate and sulfide sections are demonstrated in **Figures 18** and **19**, respectively. Also, the archived tonnage-grade parameters from the IDW method in carbonate and sulfide sections are given in **Tables 3** and **4**, separately. Moreover, **Figures 20** and **21** represented the tonnage-grade curves of SK method in the carbonate and sulfide sections, correspondingly. Furthermore, tonnage-grade variables of the IDW method in carbonate and sulfide sections are provided in **Tables 5** and **6** respectively.

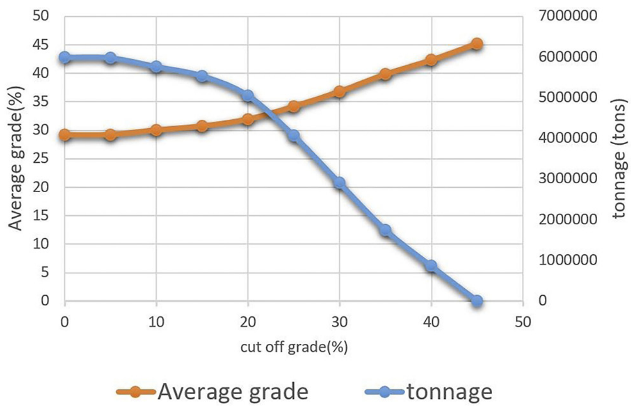

Figure 18: The tonnage-grade curves of the IDW method in the carbonate section

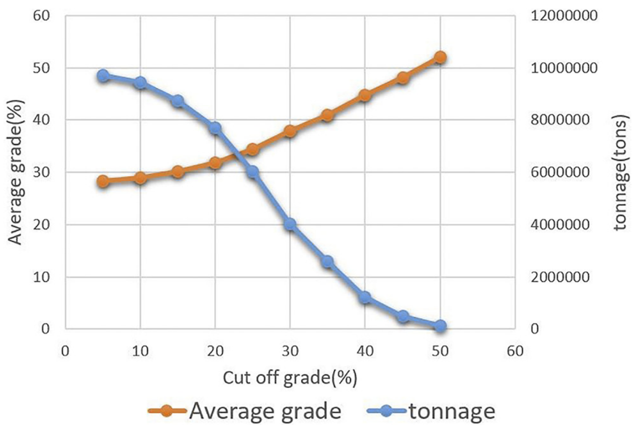

Figure 19: The tonnage-grade curves of the IDW method in the sulfide section

Table 3: The archived tonnage-grade parameters from the IDW method in the carbonate section

Cut-off grade (%)	Average grade (%)	Tonnage (ton)
5	28.31445629	9711750
10	28.90810342	9429562.5
15	30.20528739	8745000
20	31.90986602	7702500
25	34.47613193	6022312.5
30	37.87354563	4027500
35	40.98781924	2586562.5
40	44.75582564	1223625
45	48.17295407	515062.5
50	52.13144968	133875

Table 4: The archived tonnage-grade parameters from the IDW method in the sulfide section

Cut-off grade (%)	Average grade (%)	Tonnage (ton)
0	29.18349091	000643.75
5	29.23807239	5987412.5
10	30.04221442	5770637.5
15	30.74560192	5544256.25
20	31.94458012	5061950
25	34.19482471	4074862.5
30	36.82721421	2911600
35	39.87065917	1757943.75
40	42.36056541	869275
45	45.28529775	19212.5

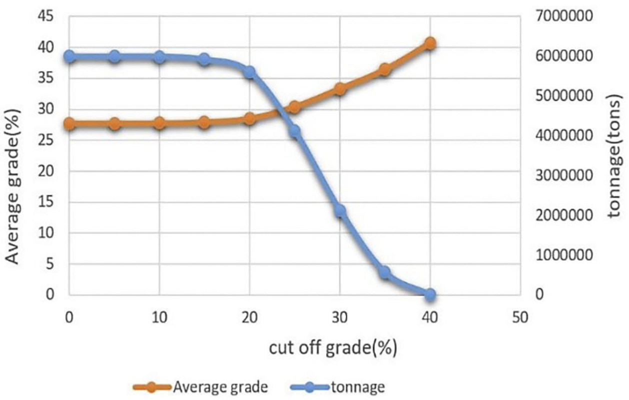

Figure 20: The tonnage-grade curves of the SK method in the carbonate section

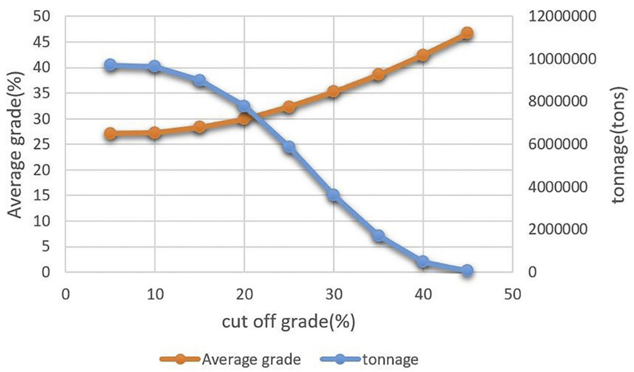

Figure 21: The tonnage-grade curves of the SK method in the sulfide section

Table 5: The archived tonnage-grade parameters from the SK method in the carbonate section

Cut-off grade (%)	Average grade (%)	Tonnage (ton)
0	27.77467525	6000643.75
5	27.78138837	5999193.75
10	27.79339921	5995206.25
15	27.96085737	5924700
20	28.53897592	5611137.5
25	30.45448879	4131956.25
30	33.38242047	2133493.75
35	36.48692666	573656.25
40	40.76611022	12325

Table 6: The archived tonnage-grade parameters from the SK method in the sulfide section

Cut-off grade (%)	Average grade (%)	Tonnage (ton)
5	27.13458648	9711750
10	27.27449377	9636750
15	28.29446958	8993812.5
20	29.92977268	7791187.5
25	32.27117016	5876250
30	35.29619789	3601500
35	38.60319997	1711125
40	42.43492296	481312.5
45	46.67693832	72187.5

6. Validation of reserve estimates

In order to validate the resource estimations in this study, comparing the estimated results of the IDW and SK methods with the exploratory boreholes and extracted blocks is used. **Figures 22** and **23** demonstrate the correlation diagrams between the estimated blocks from IDW method and exploratory boreholes in carbonate and sulfide sections, respectively. Also, comparisons between the IDW results and exploration boreholes in the carbonate and the sulfide sections are represented in **Figures 24** and **25**, correspondingly.

In addition to the borehole validation, the resource estimated parameters by the IDW and SK methods are further compared with the information of the extracted blocks in the Angouran open pit mine. Also, the obtained results are compared with previous resource estimations in the Angouran Mine in the local coordinate system. Based on this comparison, the smaller the difference, the better the IDW and SK results because all the extracted block information is accurate and clear. This comparison is conducted for two extraction steps with a height of 30 m. The information of extracted steps is given in **Table 7**. Also, the information of resource estimation by IDW, SK and the previous resource estimation in the Angouran Mine are presented in **Tables 8-10**, respectively. According to these results, the error values of the estimated average grade from the current and previous re-

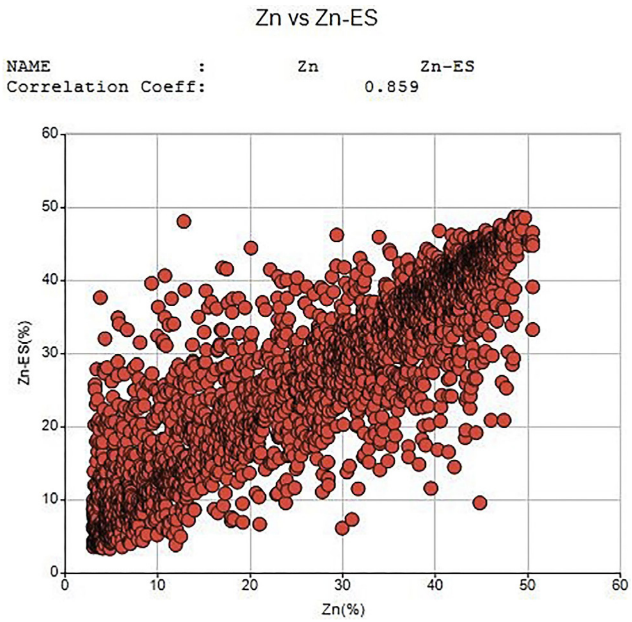

Figure 22: Correlation between the IDW results and exploratory boreholes in the carbonate section

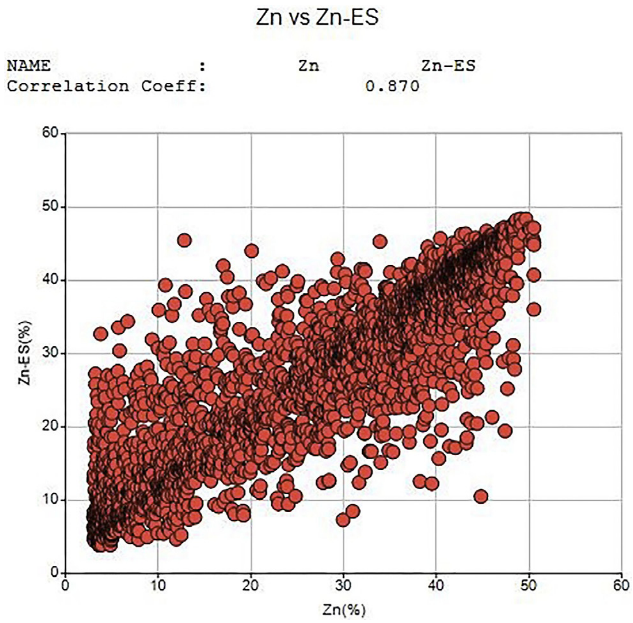

Figure 24: Correlation between the SK results and exploratory boreholes in the carbonate section

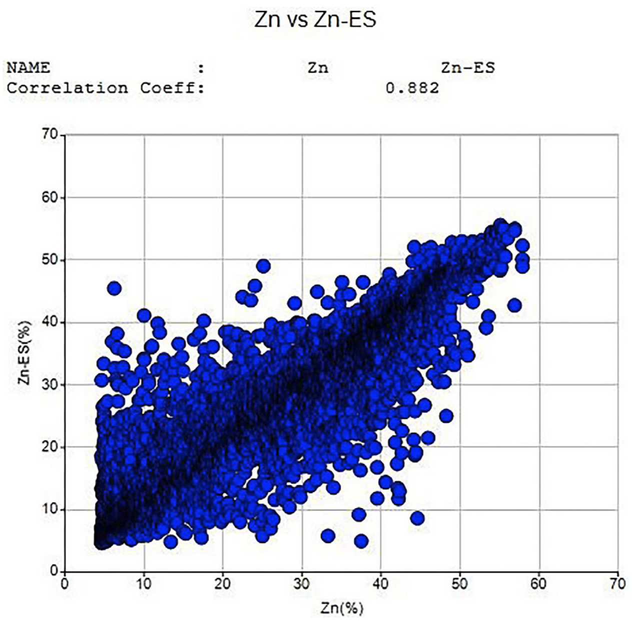

Figure 23: Correlation between the IDW results and exploratory boreholes in the sulfide section

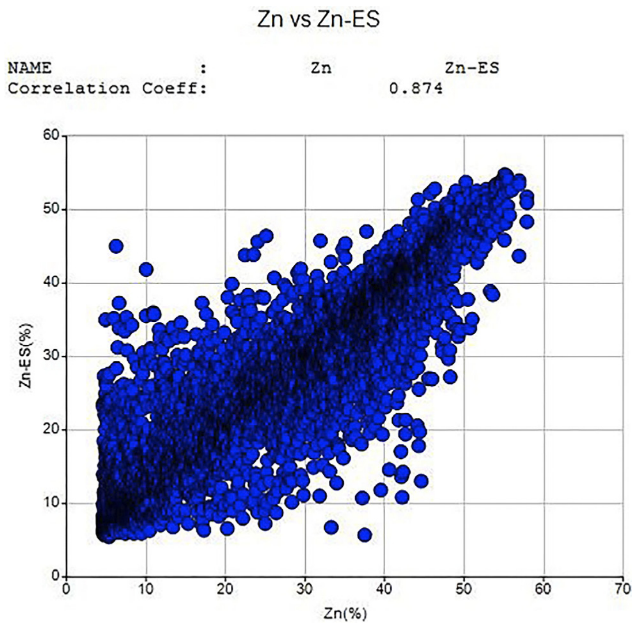

Figure 25: Correlation between the SK results and exploratory boreholes in the sulfide section

Table 7: Information of the extracted blocks

Height of extraction step	Average grade (%)	Density	Volume (m^3)	Tonnage (tons)
2479 to 2509	21.6	2.9	379310.345	1100000
2509 to 2539	18.5	2.9	310344.828	900000

Table 8: Information of the estimated block model by the IDW method

Height of extraction step	Average grade (%)	Density	Volume (m^3)	Tonnage (tons)
2479 to 2509	26.84	3	496000	1488000
2509 to 2539	23.77	2.9-3	385312.5	1155387.5

Table 9: Information of the estimated block model by the SK method

Height of extraction step	Average grade (%)	Density	Volume (m^3)	Tonnage (tons)
2479 to 2509	26.61	3	496000	1488000
2509 to 2539	23.02	2.9-3	385312.5	1155387.5

Table 10: Information of the previous resource estimation in the mine (local coordinate system)

Height of extraction step	Average grade (%)	Density	Volume (m^3)	Tonnage (tons)
2790 to 2820	31.55	3.15	419509.62	1323195.36
2820 to 2850	27.50	3.06	442048.67	1356812.30

Table 11: Error of the current and previous resource estimations for average grade evaluation

Height of extraction step	SK error (%)	IDW error (%)	Previous reserve estimation error (%)
2479 to 2509 (Sulfide section)	23.1	24.2	46
2509 to 2539 (Carbonate section)	24.4	28.49	48.6

Table 12: Errors of the current and previous resource estimations for tonnage evaluation

Height of extraction step	SK error (%)	IDW error (%)	Previous reserve estimation error (%)
2479 to 2509 (Sulfide section)	35.27	35.27	50.29
2509 to 2539 (Carbonate section)	28.37	28.37	50.75

source estimations are presented in **Table 11**. Furthermore, the percentage error of estimated tonnage from the current and previous resource estimations are presented in **Table 12**. From these comparisons, it can be seen that the grade and tonnage estimations from the previous resource estimation and new resource modeling in the mine are higher than the actual grade and tonnage. However, estimation errors of both grade and tonnage variables are decreased in this study compared to the previous resource estimation in the mine. Also, it is proven that the accuracy of the current resource estimation is acceptable compared to the exploratory borehole and extracted block information.

7. Conclusions

Optimization of the block model and accurate resource estimation of the Angouran Mine were conducted in this research. For this aim, the mine exploratory database was initially transferred from the local coordinate system to the UTM. Variography in three directions proved the geometrical and regional anisotropies in the database. After that, waste blocks were removed and the block model optimization was done using the IK method. Lastly, resource estimation in both the carbonate and sulfide sections was conducted using the IDW and SK approaches. The achieved correlation coefficient of IDW, SK and IK is 0.86, 0.87 and 0.92, and 0.88, 0.87 and 0.92 in carbonate and sulfide sections, respectively. This confirmed the acceptable accuracy of the utilized resource estimation methods. For more validation of the applied resource estimation methods, their obtained average grades and tonnages are contrasted with the information of exploratory boreholes, mined blocks and previous resource estimation results. A comparison of the results showed satisfactory accuracy of the used estimation approaches. Also, higher correlation and lower error of the suggested resource estimation methods compared to the mine previous resource estimation was proven in estimating the tonnage and average grade. In-situ verification proved that both previous and new estimations are over-estimated in which the error of grade and tonnage estimations in the previous resource modeling are 46% and 50.75%, respectively. However, in the new resource modeling, these errors are reduced to 23.1% and 28.37%, respectively. These comparisons confirmed the reliability of the proposed methodology in this study for resource estimation of the Angouran Mine. Finally, it can be concluded that transferring the exploration database from the local coordinate system to the UTM and removing the waste blocks in block modeling can enhance the accuracy of resource estimation.

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SAŽETAK

Optimizacija blok-modela i procjena rezervi rudnika Angouran pomoću prebacivanja istraživačkih podataka iz lokalnoga u UTM koordinatni sustav

Procjena rezervi jedan je od najvažnijih koraka u rudarstvu. Precizna procjena rezervi ima znatan utjecaj na optimizaciju budućih rudarskih zahvata, odnosno na planiranje i razradu rudnika. Procjena rezervi u rudniku Angouran načinjena je uporabom lokalnoga koordinatnog sustava za koji je ocijenjeno kako je prouzročio znatne pogreške. Zbog toga je ovim istraživanjem prikazana optimizacija blok-modela rudnika te izračun rezervi u UTM (univerzalna transverzalna Mercatorova projekcija) globalnome koordinatnom sustavu. Istraživački podatci najprije su prebačeni iz lokalnoga u UTM koordinatni sustav. Zatim je načinjena optimizacija blok-modela pomoću indikatorskoga krigiranja (IK) kojim su ocrtani uklonjivi jalovinski blokovi i tako optimiziran blok-model. Konačno, procjena rezervi provodi se metodom inverzne udaljenosti (IU) i jednostavnoga krigiranja (JK). Variogramskom analizom u različitim smjerovima utvrđena je anizotropija rudnoga ležišta. Također, rezultati validacije pokazali su kako koeficijent korelacije za IU, JK i IK prosječno iznosi 0,86, 0,87 i 0,92 za karbonatne, odnosno 0,88, 0,87 i 0,92 za sulfidne dijelove ležišta. Na kraju su procijenjeni sadržaj i količine rude uspoređene sa stvarnim podatcima iz istraživačkih bušotina, odminiranih blokova i prethodne procjene rezervi u rudniku. Usporedba je pokazala kako su sadržaj i količine rude iz prethodnoga, ali i novoga modela precijenjene, odnosno više od stvarnih vrijednosti. Međutim, minimalne pogreške u procjeni sadržaja rude iznose 46 % za prethodno utvrđene rezerve, no znatno manjih 23,1 % kod novoga izračuna (prije i nakon uklanjanja jalovine). Također, istovrsne pogreške procjene za količinu iznose 50,29 % za prethodni, odnosno 28,37 % za novi model. Terenska usporedba dokazala je kako prebacivanje istraživačkih podataka u UTM sustav, korištenje IK-a za uklanjanje jalovinskih blokova i primjena JK-a za procjenu rezervi dovode do optimizacije blok-modela i smanjenja pogreške izračuna rezervi u rudniku.

Ključne riječi:
procjena rezervi, UTM, indikatorsko krigiranje, jednostavno krigiranje, metoda inverzne udaljenosti

Author's contribution

Mohammad Rezaei (Associate Professor, Ph.D., Mining Engineering) provided the idea and methodology, conceptualization, visualization of the data, interpretations and presentation of the results, research management, and writing, reviewing and editing the paper. **Siavash Fallahi** (Graduate, MSc., Mining Engineering) performed the field work, contributing with the Angouran Mine geology and exploration teams, data representation, software analysis and modelling, and writing the original draft.