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Determination of Final Pit Depth of the Western Part of the Aynak Copper Deposit by Surpac and NPV Software

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Abstract

This study discusses the use of Surpac and NPV Scheduler software to determine the pit depth of the western part of the Aynak copper deposit. Despite exploratory boreholes in this area, the final pit depth has not yet been determined. Post-processing drilling data was used to model the deposit in Surpac, and the resulting model was imported into NPV Scheduler. Considering economic parameters, optimization was performed to determine the final pit limit and mining depth. The findings show that the optimal final pit depth is 540 meters. At this depth, the extractable reserve is estimated to be 57,353,400 million tons, with a cut-off grade of 0.3% and a stripping ratio of 1:4; open-pit mining is economically justified. These results can serve as a basis for decision-making in mining planning and the future development of the mine.

Keywords: Surpac, NPV Scheduler, Modeling, Optimization, Mining planning

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Introduction

The design of the final limit open-pit mining, especially the determination of the pit depth, is a complex and important issue that is used to define the location of waste dumps, the area of surface facilities, the amount of extractable reserves, and the volume of waste materials to be removed. The final depth of the mine is the economic zone, below which mining is no longer economical (Xu et al., 2024). This boundary is determined using the economic block model, prepared by considering the deposit's economic parameters. In the final limit design methods, a group of regular block networks, called the block model, is created from blocks that maximize certain parameters, such as profit, metal content, or net present value, and are used to determine the final pit limit (Mwangi et al., 2020). This model is created by interpolating data from

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drilling samples. Several estimated attributes, such as rock type, ore grade, and density, are estimated using geostatistical methods (Chiles & Delfiner, 2012).

Investment in mining projects is always associated with risks, which play a decisive role in the final profitability of projects (Haque et al., 2014). A major source of this uncertainty is fluctuations in mineral prices and production costs (Cortez et al., 2018). Classical methods for determining the ultimate pit depth are often based on the constancy of economic and geological parameters. In practice, factors such as metal price fluctuations, changes in mining and processing costs, and uncertainties regarding the grade and tonnage of the ore are dynamic and unpredictable. Ignoring these conditions over time can lead to errors in calculating the net value of the block and, as a result, suboptimal design of the final pit depth (R. Dimitrakopoulos et al., 2002). To address these variables in open-pit mines, various techniques have been proposed. For instance, a method has been introduced to assess geological uncertainty in long-term production scheduling (Gilani et al., 2020). Alonso-Ayuso et al. presented a method for optimizing copper mining planning that accounts for uncertainty in future copper prices (Alonso-Ayuso et al., 2014). In a study by Menebde, the Block Economic Value was investigated using conditional simulation techniques for the final pit depth boundaries (Said & El-Midany, 2022). The models presented by Tolana and Musingvini enable a more comprehensive analysis of the economic value of blocks under varying price conditions for optimal pit depth (Tolana & Musingvini, 2022). In a study by Albor and Dimitrakopoulos, a method was developed to simultaneously consider several factors affecting the design of a push pit (Consuegra & Dimitrakopoulos, 2010). The Real Option Based (ROV) valuation approach was proposed as a solution for analyzing mining projects under uncertain economic conditions (Dimitrakopoulos & Sabour, 2007). Baek et al. (2016) investigated the impact of price changes on the open-pit boundaries. A multi-stage stochastic planning strategy has also been proposed for production scheduling in open-pit mines with uncertain geology (Boland et al., 2008). geostatistical simulation and parametric analysis to model the impact of geological and price changes on the final scope and overall project economics (Kopacz et al., 2018). Evatt et al. (2012) proposed a method for estimating mineral reserves under uncertain mineral price conditions. The success of mining projects is influenced by several factors, including economic, technical, and ESG (environmental, social, and governance) considerations (Fu et al., 2024). Neglecting these parameters may lead to errors in mine design and economic evaluation, ultimately resulting in suboptimal and non-operational production plans (Kasa & Dağ, 2022).

Several algorithms have been proposed to solve the final problem of the pit depth, like exact mathematical algorithms, heuristic and meta-heuristic algorithms, and dynamic programming methods. Exact mathematical algorithms, such as the graph-theory-based Lerch-Grossman (1965) method, Johnson's (1967) network flow, and Gianini's (1990) maximum flow–minimum cut algorithms, provide optimal final boundaries with mathematical guarantees (Kaydım, 2022). However, solving large and complex problems with these methods is difficult and time-consuming.

Heuristic and meta-heuristic algorithms, such as the floating cone and its improved versions (Deutsch, 2023). Alternatively, genetic algorithms and neural networks (Chiroma et al., 2017) focus on search logic, provide approximate answers with appropriate accuracy and in an acceptable time relative to the pit boundary, and offer high flexibility in handling variables. The dynamic programming method is also a classic approach to the design of the final boundary, first developed by Lerch-Grossman (1965) for two-dimensional models and later applied, with modifications, to three-dimensional models and to production scheduling (Mousavi Nogholi, 2015). Despite ensuring optimality, this method has implementation limitations for large-scale real-world models.

The concept of the impact of the final boundary of open-pit mines on fluctuations in mineral prices was proposed in 1965, at the same time as the introduction of the nested pit algorithm by Lerch-Grossman. This algorithm was developed to analyze and determine the optimal mining depth under changing price conditions (Petrov et al., 2021).

The Aynak copper deposit is one of the largest in Afghanistan and is comparable in grade and volume to some Zambian copper belt deposits (Azizi et al., 2015). It is located approximately 30 km south-southeast of Kabul city and within the Kabul tectonic block. Its western part is located approximately at 69°18'18″ longitude and 34°15'58″ latitude Figure 1.

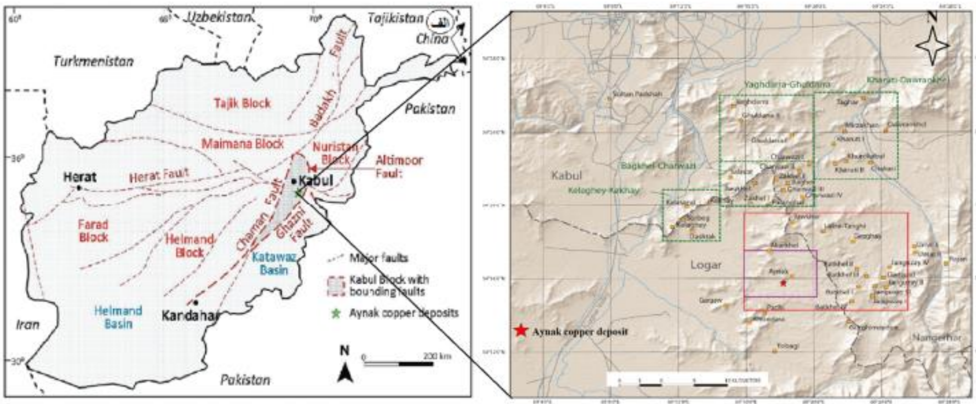

Figure 1: Tectonic map of the Kabul Block and the Aynak copper deposit (Waizy et al., 2021).

Until now, despite geological studies, the optimal depth for open-pit mining in the western part of this mine has not been systematically determined using economic indicators. This gap has led to decision-making on the final pit area and mining depth lacking analytical support aimed at maximizing the project's economic value. Therefore, in this research, in order to fill this gap, the Net Present Value (NPV) criterion has been used in the Surpac software environment. In this framework, by combining the land block model.

Methods and Materials

This research is an applied, quantitative study that aims to determine the final pit depth in the western part of the Aynak copper deposit using specialized mining software. In this research, a modeling and optimization approach has been used to evaluate the economic limits of open-pit mining.

The research framework includes several basic, continuous stages. In the first stage, geological and topographic data of the deposit were collected and processed, and then a 3D block model was created using Surpac software. This model represents the spatial distribution of grade and geological characteristics within the deposit. In the next stage, economic parameters were entered into the model. Furthermore, an optimization process was conducted to determine the final pit depth that maximizes. The main focus has been on identifying the depth at which further mining is not economically justifiable.

This research employs a quantitative approach, using numerical data and computational tools for the economic and technical analysis of the deposit. The final result of this research project is the determination of the optimal pit depth that ensures maximum economic efficiency under specific technical and economic conditions.

Research Instrumentation

This study utilized a suite of tools and software to gather, process, and model the data. Specifically, a set of specialized tools and software was used to collect, process, model, and analyze the dataset comprehensively.

The Google Earth platform has been used to provide initial spatial and topographic data. Additionally, the GPS Online system has been utilized to obtain precise geographic coordinates. Next, topography was created and modeled using specialized mining software.

The specialized mining software Surpac has been used to model the deposit and create a 3D block model. This software plays a fundamental role in analyzing the geological structure and grade distribution within the deposit (Bargawa et al., 2016).

The Scheduler software has been used to determine the optimal pit depth, taking into account the parameters defined in the geological block model, economic parameters, and operational influencing factors. This software plays an effective role in analyzing the extraction sequence and economic evaluation of the mine. Finally, Origin software was used to draw graphs and present results, enabling an accurate display of relationships among variables.

Data Collection

In this study, the exploration boreholes were first analyzed to obtain detailed geological and topographic information of the study area. The borehole data, including depth, location, and geological logs, along with surface topography, provided the foundation for accurate modeling of the deposit.

To model the ore body, cross-sections were drawn along the exploration boreholes to visualize the mineral distribution. Sectioning involves slicing the borehole data along the borehole traces to identify the geometry of mineralization. Each section represents a reflected view of the borehole information, facilitating interpretation of the ore body.

A block model is a three-dimensional digital representation of a mineralization zone that subdivides the total reserve into a regular grid of uniform, equal-sized blocks (Li et al., 2022). The model is large enough to cover the full range of input data (Bargawa & Amri, 2016). The geological block model was built from the 3D solid model, with the main specifications, including the model name, origin point, spatial extent, and block dimension, determined (Table

1). After that, important mineralization information, such as grade, density, and mineralization zone, was assigned to each block.

Table 1: *Block Model Extent*

Parameter	Dimensions along the Z-axis	Dimensions along the Y-axis	Dimensions along the X-axis
Minimum Coordinates	1360	25000	90350
Maximum Coordinates	2350	27100	92750
Main Block Dimensions	15	10	10
Sub-block Dimensions	7.5	5	5

Using a block model, the values of each block's properties are estimated from geological and borehole data, along with statistical methods. These models form the fundamental basis for reserve estimation, pit design, and mining project planning.

In this research, the semi-variogram was applied as the primary research method to describe the spatial continuity and correlation of grades within the deposit, providing the foundation for geostatistical estimation. Reserve estimation was conducted based on the variographic study by Miao et al. (2025), which is a standard approach in geostatistical research. Geostatistical methods were used to regionalize variables, assuming that deposit characteristics exhibit random behavior while also possessing spatial structure (Gill et al., 2023). The main analytical tool in this methodology, the semi-variogram, examines the spatial structure of the data and is defined as half the mean-square difference in the values of a variable over a distance h (Zerzour et al., 2020). For the Aynak copper deposit, variography operations were specifically performed as part of the research methodology to estimate reserves using spatially correlated ore grades, analyze the structural characteristics of the deposit, and determine anisotropy, including the directions of the anisotropy ellipse axes. This approach ensures that spatial patterns and continuity of the ore are accurately incorporated into the modeling and reserve estimation process, forming a core component of the research method in this study. The geostatistical method of ordinary kriging was applied to estimate mineral reserves, as it effectively accounts for spatial correlation between borehole data and reduces uncertainty (Leo, 2023). First, the drilling data were checked for accuracy, uniformity, and outliers, and necessary corrections were applied before conducting geostatistical analyses.

The characteristics of the anisotropic search ellipsoid, including the major range, minor ranges, orientation angles, and the selected variogram model, were defined and are summarized in Figure 2. These parameters were used as key inputs in the block modeling and grade estimation processes within the Surpac environment. Furthermore, they were applied in the design of the optimal final pit boundary and play a significant role in improving the reliability of the reserve estimation (Rezaei et al., 2019).

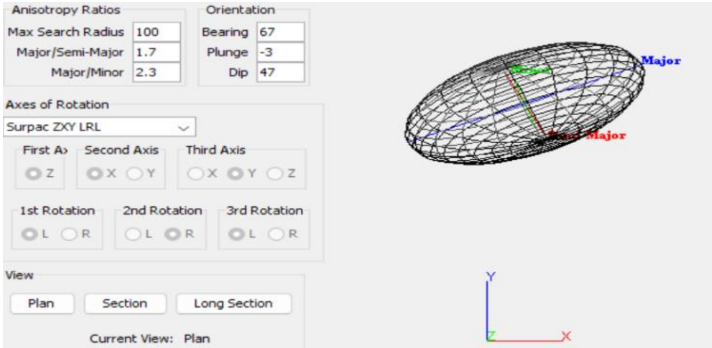

Figure 2: *The anisotropic search ellipsoid used in the kriging Method within the Surpac environment.*

To determine the final pit limit, the NPV Scheduler software was utilized. Initially, economic and geological parameters, including metal prices, operating costs, discount rates, and grade data, were imported into the software as input variables (Table 2).

Table 2: *Block Model Parameters for Optimal Pit Design Using Surpac and NPVs*

Parameter	Parameter	Value
Geological	Ore density	2.85(ton/m³)
	Waste density	2.76(ton/m³)
	Final pit slope angle in all directions	47°
Economic	Pure Copper price	9000($ /ton)
	Ore mining cost	2.25 ($ /ton)
	Waste mining cost	1.5 ($ /ton)
	Mining recovery	97%
	Processing recovery	87.5%
	Smelting and refining recovery	97%
	Dilution	5%
	Discount rate	10%
	Ore Processing cost	7.32 ($ /ton)
	Smelting and refining the cost of pure copper	400 ($ /ton)

(Source: Mirzaian et al., 2024)

An initial pit shell was then generated, representing the economic extraction boundary under ideal conditions. Subsequently, the optimization process was performed using the Lerchs–Grossmann algorithm to identify the most economically optimal pit limit. This algorithm evaluates the economic value of each block and selects those with positive value to define the optimal pit boundary (Joshi et al., 2022). Finally, the optimal pit depth and boundary were determined by maximizing Net Present Value (NPV) while accounting for technical and operational constraints. A summary of the conversion process is shown in Figure 3 below:

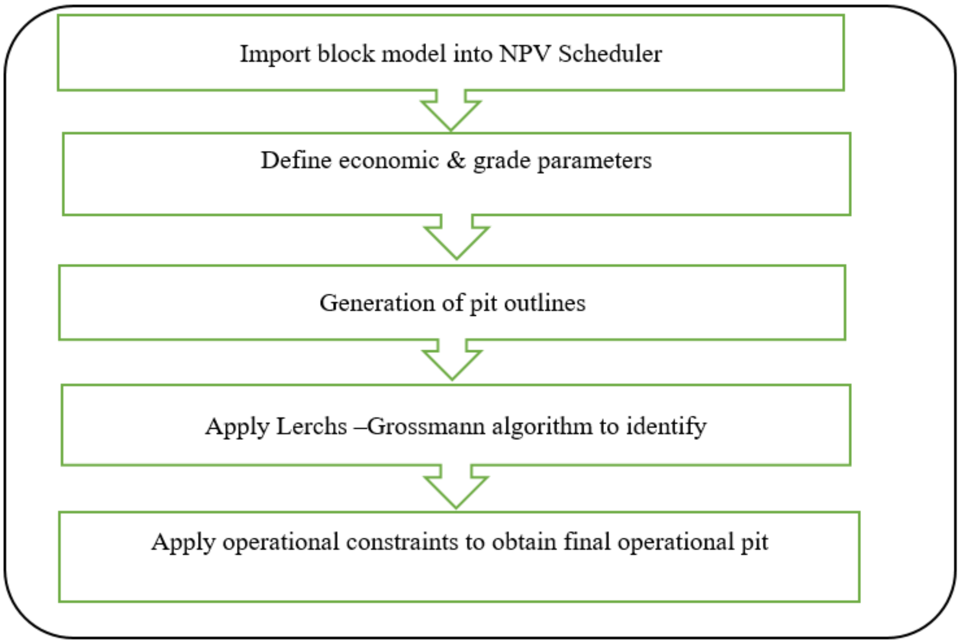

Figure 3: *Flow Chart of Optimisation in NPV Scheduler.*

Data Analysis

In this study, exploration data from 24 boreholes with a total length of 11,902 meters were used to determine the open-pit depth in the western part of the Aynak copper deposit. The collected dataset included Collar, Geology, Survey, and Assay information, which were prepared and organized for further processing in Surpac software. The borehole data were structured into four separate CSV files, namely Assay, Collar, Survey, and Geology, to ensure compatibility with the modeling environment. Spatial coordinates (X, Y, and Z) were utilized to represent the location, elevation, and geometric consistency of the drilling data.

The exploration datasets were processed and prepared to support geological modeling. Using available data, preliminary analyses were conducted, including geological interpretation, block modeling, and open-pit depth calculations. These steps ensured that subsequent modeling and optimization were based on reliable and systematic information.

Due to confidentiality constraints, the Assay and Geology datasets were limited, whereas the Collar and Survey datasets contained complete information for all boreholes. These limitations were taken into consideration during the interpretation of results. Nevertheless, the provided datasets are sufficient to support subsequent geological modeling and pit design procedures in Surpac, and their details are presented in Table 3 below.

Table 3: *Western part of the Aynak copper deposit borehole data*

BH-ID	Y	X	Z	Dip	Azimuth	Depth(m)	`Depth From (m)	Depth To (m)	Cu (%)
BH201	25537.47	91401.21	2344.158	-50	160	237	127	129.14	0.92
BH301	25622.28	91460.77	2309.48	-82	160	408	89.6	92	1.27
BH302	25642.63	91404.99	2316.144	-81	160	351	148.5	150	1.1

BH401	25718.55	91488.7	2279.59	-68	160	356	186.68	188.6	1.14
BH501	25780.94	91609.76	2335.23	-76	160	646	480.06	482.56	0.54
BH502	25868.26	91369.6	2291.78	-75	160	168	14.4	15.9	0.29
BH601	25925.97	91507.47	2299.8	-87	160	661	59.36	61.85	0.81
BH602	25929.76	91493.14	2299.406	-50	160	283	16.1	18.98	0.61
BH702	26016.66	91546.73	2302.48	-81	160	651	483.48	485.4	0.69
BH703	26049.45	91454.71	2305.376	-73	160	486	4.2	6.7	0.26
BH802	26102.93	91602.02	2297.1	-74	160	671	348.29	350.5	0.33
BH1002	26319.67	91591.36	2303.72	-72	160	619	833.6	836	0.36
BH1202	26367	91686	2314.37	-70	160	643	286.19	288.1	0.24
D272	26361	91626	2308.5	-77	160	536	316	318	0.57
BH603	26156.55	91747.13	2303.45	-74	160	953	186.68	188.6	1.14
BH701	26278.34	91704.9	2311.46	-82	160	874	480.06	482.56	0.54
BH901	26797.77	92036.29	2339.834	-79	160	330	124.2	126.7	0.26
BH902	26019.26	91543.17	2309.48	-82	160	558	348.29	350.5	0.38
BH1001	26098.75	91318.17	2239.03	-75	160	326	234.2	236.2	2.3
BH1601	26408	91899.8	2344.158	-83	160	318	315.8	317.8	0.24
D285	26415.56	91925.07	2309.48	-76	160	569	540	423	0.31

Findings

Demographic Characteristics

In this section, the demographic characteristics of the research population, including gender, age, and education level, are analyzed for the 148 participants.

Gender

Table 4 and the table below present the frequency distribution of the study sample by gender.

Table 4: *Frequency Distribution of the Sample Based on Gender*

Gender	Frequency	Percentage
Male	80	54%
Female	68	46%
Total	148	100%

Out of a total of 148 subjects, 80 (54%) were males and 68 (46%) were females. This demonstrates a slight predominance of male subjects in the sample. The distribution shows a reasonably balanced representation of both genders, facilitating a detailed analysis of gender-based differences in the study.

Age

Table 5 presents the distribution of the sample by age, frequency, and percentage of individuals per age group.

Table 5: *Age Distribution of the Sample*

Age	Frequency	Percentage
Less than 30	5	3%
31 to 40 years	30	20%
41 to 50 years	45	31%
51 to 60 years	40	27%
Over 61 years	28	19%
Total	148	100%

Among the 148 respondents, the most significant percentage, 31%, is among 41- to 50-year-olds, comprising 45 individuals. This is followed closely by the 51- to 60-year-olds, who make up 27% of the sample and 40 individuals. The 31 to 40-year-old age group comprises 20% of the total, or 30 individuals. Over 61 years of age accounts for 19% of the sample (28 individuals), while individuals under 30 years old account for merely 3% (5 individuals). Figure 2 presents the age distribution of the respondents.

Education

Table 6 shows the frequency distribution of the sample by education level, including the number and percentage of individuals in each category. The majority of respondents (33%, 49 individuals) have a master's degree. This is followed by a PhD, where 25% of the sample consists of 36 individuals. Participants holding an associate degree make up 22% of the sample (33 participants), while those holding a bachelor's degree make up 20% (30 participants).

Table 6: *Frequency Distribution of the Sample Based on Education Level*

Education Level	Frequency	Percentage
Associate Degree	33	22%
Bachelor's Degree	30	20%
Master's Degree	49	33%
PhD	36	25%
Total	148	100.0%

Findings

Borehole Configuration and Topographic Modeling Results

The data from 20 drill holes accurately represent the geometry and shape of the orebody. After database validation, the spatial distribution of the drill holes was analyzed in 2D and 3D views. Figure 4, the 3D visualization, clearly shows the vertical continuity and spatial arrangement of the boreholes within the study area.

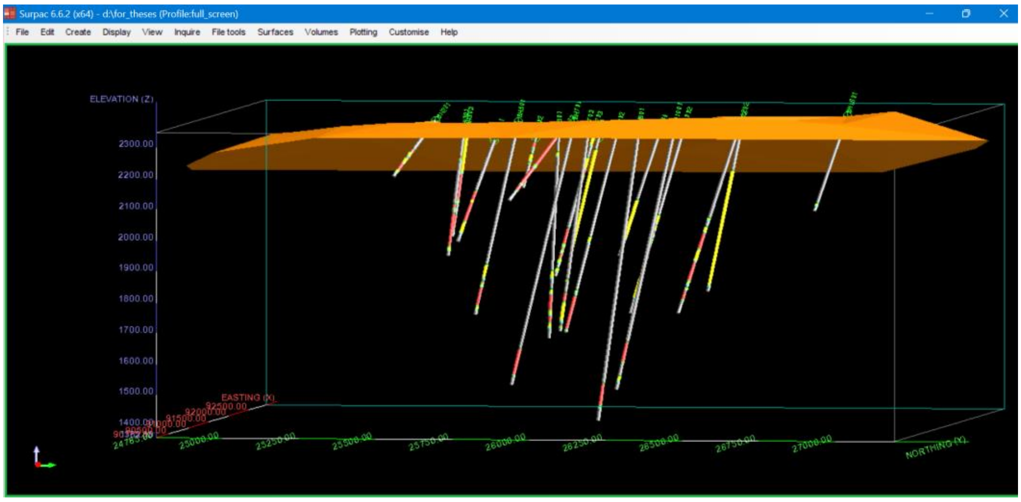

Figure 4: A 3D view of boreholes and the topography of the study area obtained from Surpac software.

Solid Model of Orebody Results

A 3D solid model of the orebody in the western Aynak deposit was constructed in Surpac using drilling data and geological interpretation. The wireframe and solid views in Figure 5 clearly illustrate the reservoir geometry, geological boundaries, and grade distribution, with higher-grade zones aligned along major structures. Eight geological sections were created at regular intervals in the north direction (x–z plane) to define the mineralized areas for digital modeling. This solid model provides a reliable basis for reserve estimation, pit depth determination, mine design, and conversion to an economic block model (Wei et al., 2025).

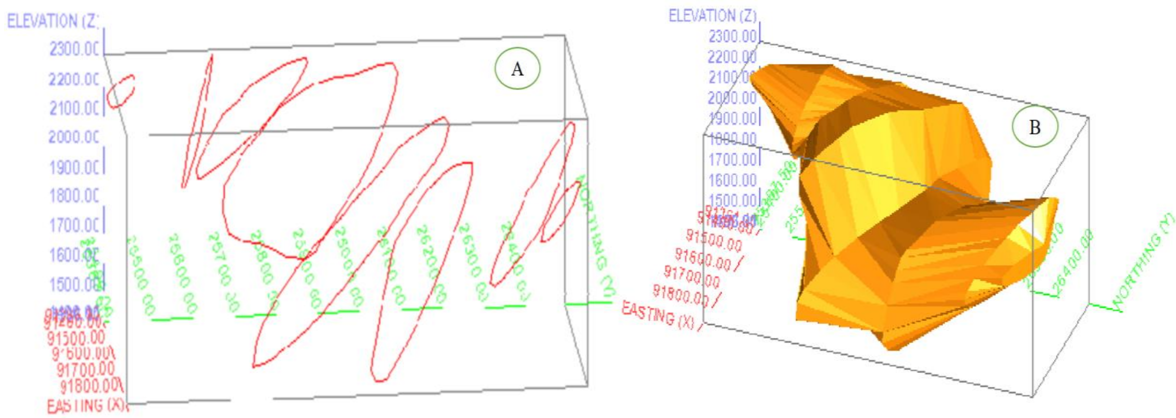

Figure 5: Geological model of the study area in Surpac environment: (a) wireframe; (b) solid model.

Variogram Analysis Results

To evaluate the spatial variability of the data, empirical variograms were calculated and plotted. The results of the variogram indicate that, with increasing distance, spatial correlation decreases, and the variability pattern of the studied variable is clearly evident. This behavior indicates a specific spatial structure in the data and suggests that the mineralization grade is a function of distance and direction. Comparison of the calculated variograms in different directions showed that the correlation range differs across directions, indicating anisotropy in the deposit (Tholana, 2021).

To identify the anisotropy of spatial variability, semi-variograms were calculated in different directions. Analysis of directional variograms provides a better understanding of the geometric extent of the deposit and helps identify geometric and regional anisotropy (Buelga Díaz et al., 2022). In this study, the empirical variogram was calculated based on the classical geostatistical relation (Antunes & Albuquerque, 2013):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \qquad (1)$$

where γ(h) denotes the variogram for denotes the variogram for an interval lag distance class h, N(h) represents the number of pairs for an interval lag distance class h, and $z(x_i)$ and $z(x_i + h)$ are the values of the regionalized variables of interest at locations xi and xi+h, respectively. The variogram model selected is summarized in Figure 6.

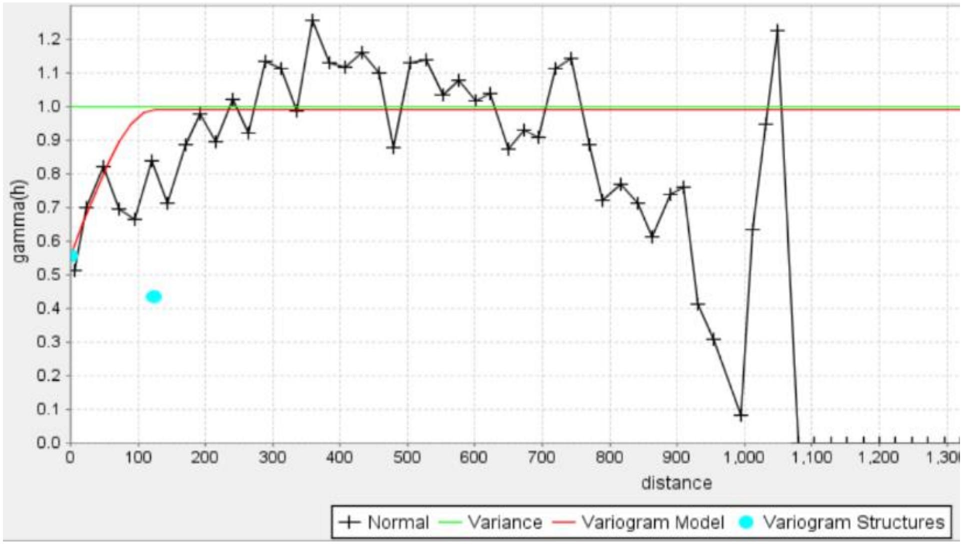

***Figure 6**: Directional variogram of the study area analyzed using Surpac software.*

Based on the directional variogram analysis, an anisotropic search ellipsoid was defined better to represent the true spatial dispersion pattern of the data. This ellipse shows the dominant direction of correlation and the main trend of mineralization development, and it plays a key role in determining the search parameters in the subsequent stages of estimation (Degterev, 2026). Aligning the estimation process with the natural geological structure increases estimation accuracy and reduces prediction error.

Results of Unit Block Modeling and Reserve Estimation

Reserve estimation was conducted to determine the final pit depth, a key step in the mine design process (Khorram et al., 2021). The Surpac-based block model consists of 147,840 blocks, of which 3,440 are ore blocks, 136,675 are waste blocks, and 7,725 are air blocks located above the topographic surface (Figure 7). This classification demonstrates that the block model fully covers the study area and aligns with the actual geological and topographic conditions.

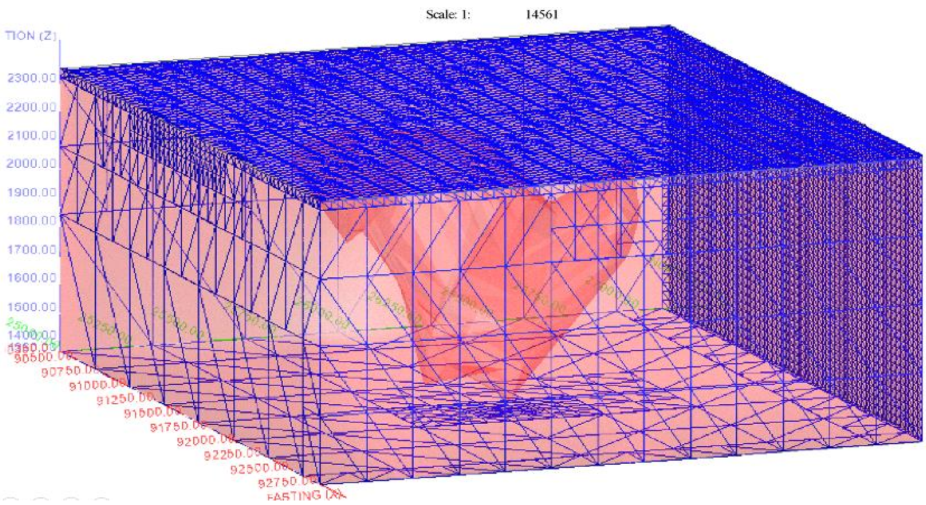

***Figure 7*:** *Block model of the study area, including the ore body, generated using Surpac software.*

In order to separate the mineral from the waste, a cut-off grade of 0.2% copper was considered (Shafayi & Torab, 2022), so that blocks with a grade lower than this value were classified as waste, and blocks with a grade equal to or higher than this were classified as mineral. The results of this classification are clearly shown in Figure 8:

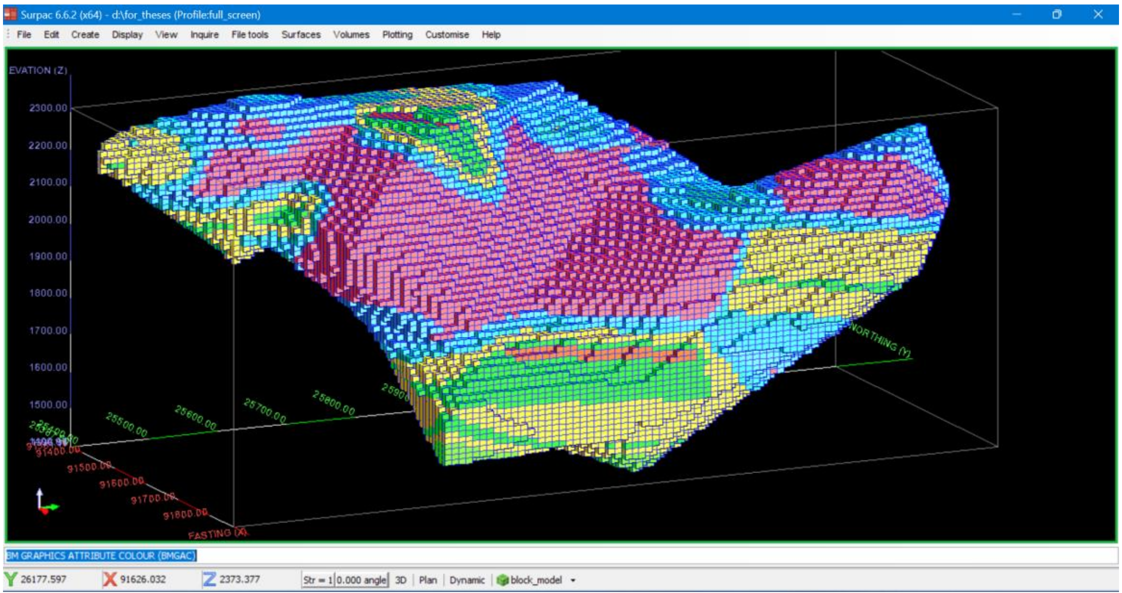

Figure 8: *Estimated mineral reserves from Surpac software, shown with color grade*.

The block grades were estimated using Ordinary Kriging, a common and reliable method for estimating mineral reserves due to its ability to account for the spatial structure of the data (Malanchuk et al., 2024).

The results of applying the Ordinary Kriging method indicate that the generated block model reflects the spatial distribution of grades in a regular manner and is consistent with the region's geological structure. The continuity of grades across neighboring blocks is well preserved, and higher grades are mainly observed in areas with higher drilling density. The estimation results also indicate that sharp grade changes are reduced compared to the raw data, and the estimated values are more stable.

The reduction of grade fluctuations in the estimation results has created a smoothing effect in the block model. Although this feature increases the reliability of the reserve estimate, it can lead to underestimation of very high-grade values. Therefore, the interpretation of the results should be based on the limitations of this method and the quality of the variogram model. In general, Ordinary Kriging provides a suitable and reliable framework for reserve estimation. The results of Ordinary Kriging can serve as a reliable basis for mine design and pit depth determination in the western part of the Aynak deposit. The outcomes of the reserve estimation are presented in Figure 9:

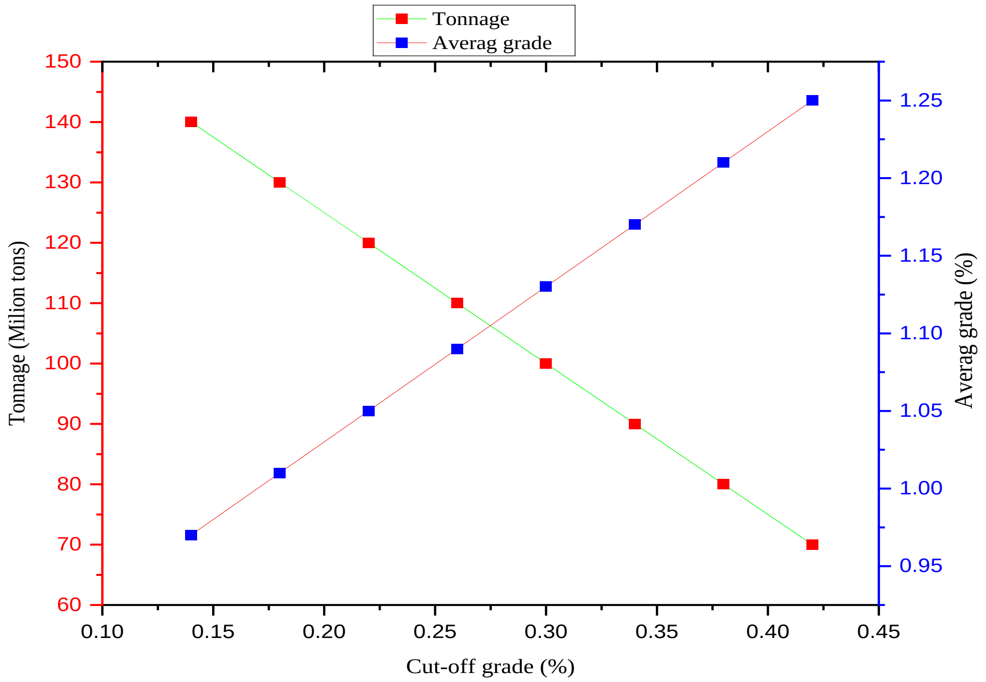

Figure 9: *Grade-tonnage curves constrained based on OK*

Finally, the estimated block model was used as input for the initial pit design, and the final pit boundary was determined based on the Net Present Value (NPV) criterion. The results indicate that the accuracy of the block model and reserve estimation directly affects the final pit depth and optimal mining boundary, with potential implications for economic outcomes and overall mine design (Yu et al., 2025).

Determining the Final Pit Depth Using NPV Scheduler

The results of the NPV Scheduler analysis indicate that the optimal economic pit limit in the western part of the Aynak copper deposit is approximately 587 meters deep. At this depth, the Net Present Value (NPV) reaches its maximum, while the stripping ratio and economic grade remain within acceptable ranges. Increasing the pit depth beyond this level results in a significant increase in waste extraction costs, reducing NPV. Therefore, this depth is considered the optimal and economic final pit limit under current conditions. The generated pit shell for the western part of the Aynak copper deposit is illustrated in Figure 10.

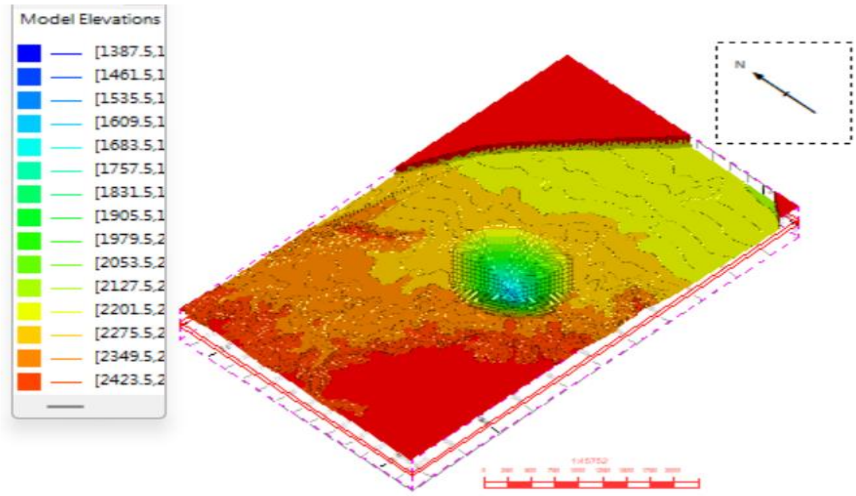

Figure 10: Pit shell of the western part of the Aynak copper deposit derived from NPVs.

Final Pit Depth of the Western Section of the Aynak Copper Mine

Based on the results of the NPV optimization, the final economic pit depth in the western part of the Aynak copper mine was determined using the NPV Scheduler software. The economically optimal depth is approximately 587 meters; however, considering technical constraints, safety requirements, and operational design limitations, the practical final pit depth is limited to about 540 meters. Based on this depth, the final pit design was carried out, and the operational pit view, including ramps and safety berms, is shown in Figure 11. Evaluation of the designed pit indicates that wall stability, pit geometry, and operational access are safe and suitable for open-pit mining. The quantitative outputs of the NPV optimization, including the amount of mineral reserves, waste tonnage, and stripping ratio, are presented in Table 4.

Table 7: *NPV-Derived Optimal Pit Results for the Western Section of the Aynak Copper Mine*

Parametr	Volume (m3)	Tonnage (t)	Cut-off grade (%)
Ore	20124000	57353400	0.3
Waste	86030100	240884280	
Total	106154100	298237680	
Stripping Ratio: 1/4			

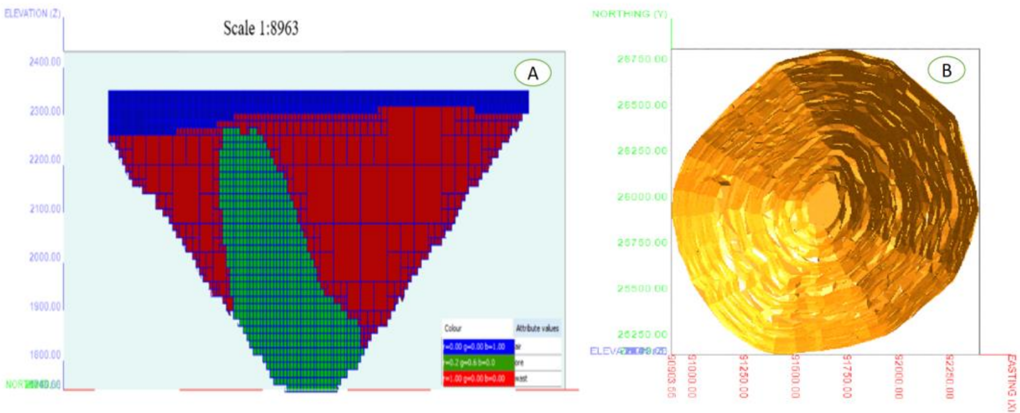

Figure 11: *(a) Vertical section derived from the block model showing pit depth; (b) operational pit plan view.*

Discussion

Analysis of 24 boreholes showed that the distribution and density of boreholes were sufficient to represent the geometry and vertical continuity of the deposit in the western part of the Aynak copper deposit. 3D visualization and solid modeling provided a clear view of the deposit geometry, geological boundaries, and high-grade areas, which are mainly located along major structures. These models provide a reliable basis for reserve estimation and determine optimal depth.

Variogram analysis showed that the deposit's spatial variation is anisotropic and that grade distribution depends on distance and direction. The use of directional variograms and the definition of anisotropy search ellipses enabled better alignment with the natural geological structure, improving estimate accuracy and reducing prediction error.

The Ordinary Kriging method created a model of blocks that reflects the spatial distribution of grade, maintains the continuity of neighboring blocks, and reduces extreme fluctuations. This smoothing increases the reliability of the estimates, although it may slightly underestimate very high grades. Nevertheless, the block model provides a solid basis for determining the final pit depth and for economic mine planning.

A total of 57.35 million tons of ore can be economically mined in 3,440 blocks at a 1:4 stripping ratio, balancing profitability and feasibility. This boundary provides a solid basis for final pit design and production planning.

The net present value (NPV)-based optimization indicated an optimal economic pit depth of about 587 m; however, practical constraints, such as safety, wall stability, and operational design, limited the final pit depth to about 540 m. The results show that accurate borehole data, appropriate modeling, and geostatistical estimation are critical to determine an optimal pit that balances ore extraction, waste management, and economic efficiency. Overall, the combination of geological modeling, variogram analysis, and NPV-based pit design ensures that the mine plan is both technically feasible and economically optimal.

Conclusion

This research aimed to determine the final pit depth in the western part of the Aynak copper deposit using block modeling in Surpac software and economic optimization with NPV Scheduler. The block model accurately represents the deposit's geometric shape, grade distribution, and reserve amount, with sufficient accuracy, and serves as the primary basis for subsequent economic analyses.

Economic optimization of the pit was performed using NPV Scheduler software and based on the Lerch-Grossman algorithm. The results showed that although from a purely economic point of view, open pit mining of the reserve is possible to a depth of about 587meters, by considering technical, safety, and operational design requirements, including slope stability, ramp design, and tailings removal ratio, the final operational and feasible depth of the open pit was determined to be about 540 meters.

Based on the obtained results, a total of 57,353,400 ton of ore contained in 3440 blocks, with a Cut-off grade0.3%, can be economically extracted by open-pit mining down to a depth of 540 m, with a stripping ratio of 1:4. This mining bundry creates a good balance between economic profitability and feasibility and can be used as the basis for the final pit design and production planning in subsequent stages.

Finally, the findings of this study have direct application in mining planning, production scheduling, ramp and safety berm design, and decision-making regarding future mine development. It is suggested that, in future studies, more detailed geotechnical analyses and broader sensitivity analyses to changes in copper prices and mining costs be conducted to assess better the uncertainties and economic and technical risks of the project.

Authors Contributions

- Seyedullah Safi was responsible for conceptualizing and designing the study, as well as for data collection and preparation.
- Mohammad Fahim Weyaar collaborated in collecting, organizing, and preparing the data and contributed to reviewing the technical sections of the article.
- Gholam Seddiq Zaheb provided valuable insights to improve the scientific quality of the study, offering scientific opinions, analytical perspectives, and a critical review of the text.
- All authors read and approved the final version of the article.

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