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APPRAISING ECONOMIC UNCERTAINTY IN OPEN-PIT MINING BASED ON FIXED AND VARIABLE METALLURGICAL RECOVERY

Given that a source is located underground and detected by sounds that cannot be completely known or predicted, every stage of the operation from grade changes to product sales exhibits uncertainties. Parameters and constraints used in mining optimizations (sales price, costs, efficiency, etc.) comprise uncertainties. In this research, chrome open-pit resource optimization activities were performed in the province of Adana, Turkey. Metallurgical recovery, which is considered a constant as an optimization parameter in mining software, has been optimized as a variable based on fixed and variable values related to the waste material grade of processing. Based on scenario number 7, which yields the highest net present value in both optimizations, this difference corresponds with an additional $1.4 million, i.e., 7% minimum. When the number of products sold were compared, a difference of 25,977 tons of concentrate production was noted (Optimization II produces less than Optimization I). In summary, concentrated efficiency and economic findings show that using variable metallurgical recovery parameters in NPV estimation improves optimization success by reducing the level of uncertainty.

Keywords: Chromite; direct block scheduling; metallurgical recovery; mine optimization

1. Introduction

Mining operations are capital-intensive pursuits involving perceptive decision-making, strategic timing of each investment, and produce valuable products in the long term [1]. Geological measurement mechanisms comprise uncertainties because of the natural structure and complexity of measurement processes. These uncertainties can originate from natural formation, sampling methods and mechanical equipment and may also be caused by environmental factors. Measurements obtained in various parts of ore deposits are further subject to uncertainty for the

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stated reasons. These uncertainties have a negative impact, particularly on economic evaluation, investment, and decision-making processes [2,3].

Field examinations conducted with search methods provided information for every point of the resource because sampling within the scope of scale and possibilities determines the availability of data. The effect of uncertainty is present in all processes from detecting all dimensions of a mineral deposit investigated through drilling to extraction. From economic dimensions, the purpose function, parameters, and constraints (e.g., sales price, costs, and recovery) used in the three-dimensional optimization of the mineral reserve being examined comprised uncertainties to a certain extent. At this point, numerous uncertainties should be considered when planning the optimal open-pit operation, to minimize the overall uncertainty level [4-6].

2. Literature Survey

Numerous studies included in the literature focused on metallurgical recovery beyond basic qualitative approaches; Boisvert et al. [7] emphasize the importance of performing multivariate metal recovery and plant performance analysis by using effective statistical tools. Garrido et al. [8] used simulations to estimate copper grades and metallurgical recoveries at drilling locations, and the results were used to construct composites [8]. Freire et al. [9] evaluated metallurgical recovery by using plant tailing data in a study where chromium tailing behavior in the concentrate plant was investigated [9].

Fixed recovery, mining, and processing costs are used in conventional approaches [10,11]. By contrast, an ore body's recovery is not constant, and recovery and throughput can change if fixed costs are used [12,13]. In one of the optimization-based approaches in a recovery analysis, Moosavi and Gholamnejad [14] emphasized that the dynamic cut-off criterion must be considered when determining the optimal production pattern for open-pit mining. The findings of this study indicate that in addition to metal recovery, mining and process costs are affected by effective decision making, which enables predicting the economic life of the block during the mine life. In a study on a similar subject, the amounts of metal gained from materials sent to different processes fluctuated because of uncertainties in the grade and material type, and the metallurgical recovery varied depending on the type of material [15]. A recent optimization study revealed that metallurgical recovery and grinding performance are parameters directly affecting planned production and thus the timing of cash flows; subsequently, they directly affect predictions for the early stages of a mining operation [16].

In this study, economic parameters, such as dynamic (variable) metallurgical recovery, are focused on net present value (NPV) estimation, and the optimization of the mine site is performed. Metallurgical recovery is one of the parameters used in enamel optimization software that assumes to be constant for all blocks. To see the results at different metallurgical recovery values, it is necessary to perform an uncertainty analysis by running the optimizations with a fixed but different recovery value for each scenario or assigning a predefined distribution of recovery because of optimization and comparison of the results. In the first method, optimization periods become excessively long, and in the second method, the already obtained results of the optimization in the software are compared with the NPV results of an uncertainty analysis. By contrast, the method used here is at the initial stage of optimization, where a metallurgical recovery value is close to the actual value for the site and is based on the analysis values at hand;

this value is applied to all blocks separately, and optimization is implemented by calculating the economic values of blocks.

Therefore, significant differences are reported in the solution of scenarios planned as fixed or variable. Concentrated recovery and economic findings show that using the variable metallurgical recovery parameter in the NPV estimation improves optimization success by reducing the uncertainty level.

3. Problem Definition

The ultimate pit limit and pit economic value obtained by mining optimization software are determined following certain algorithms. In these software, parameters, such as revenue factor (RF), cut-off grade, and metallurgical recovery, are commonly taken in certain patterns for the quarry economic value, and in particular, metallurgical recovery is considered a constant value throughout the entire quarry life. In this study, instead of a fixed metallurgical recovery or constant metallurgical recovery value, the study was performed to come up with a projection based on the feeding and tailing analysis obtained from the quarry that depended on the ore structure of the pit; this projection was then applied to the grade of all blocks. A metallurgical recovery value was found for each block. The projection plot was made for small ores, and the results were compared to observe the economic value of the quarry and compare ultimate quarry limits.

4. Methodology

4.1. Metallurgical Recovery

Many approaches can be used to increase recovery in integrated mining and metallurgical solutions. One of the approaches is to determine the optimal strategy for producing concentrates from ore. Resources, infrastructure, mining site, processing, and metallurgy are interdependent and positively interact with one another in mining and metallurgical operations [17].

Between the input grades of minerals and output grades, equality of the metal balance is observed. This equality can be expressed as follows [18]:

$$F \cdot f = C \cdot c + T \cdot t \qquad [1]$$

In Equation [1], C represents concentrate quantity (tons), c represents concentrate grade (%), F represents feed quantity (tons), f represents feed grade (%), T represents tailing quantity (tons), and t represents tailing grade (%).

The aim is to produce value at the highest quality from the raw material entering the process [19]. The recovery rate (R recovery) is defined as the ratio of precious metal weight in the concentrate to precious metal weight in the run-of-mine ore and is generally expressed in percentage [18].

$$\% Recovery = R = \frac{C \cdot c \cdot 100}{F \cdot f} \qquad [2]$$

In Equation [2], considering the equality of material balance, recovery is defined as follows:

$$\%Recovery = R = \frac{c\left(f-t\right)\cdot 100}{f\left(c-t\right)} \qquad [3]$$

Rearranging Equation [2], the quantity of concentrate can be determined as follows:

$$C = \frac{F\cdot f\cdot R}{c.100} \qquad [4]$$

4.2. Direct Block Scheduling

The mine planning process is based on the timetables of more blocks to produce over time and the development of long-term programs by assigning targets to the blocks. This programming is subject to various accounting and strategic constraints (processing capacity and slope inclination angles).

It is usually aimed at optimizing the value of the project expressed in NPV [20].

This task can be completed using two main approaches. The first is based on the Lerch-Grossmann (LG) algorithm, which generates nested pits [21]. The second approach is based on direct block scheduling (DBS), which entails taking the economic values of blocks within the framework of constraints and directly assigning production periods to the blocks through a fundamental optimization problem. The primary features of DBS are as follows:

1. Integer programming is how it is expressed. The system is limited by slopes, mining, and processing. The goal is to maximize the discounted value of production over time by determining the optimal location for each block.
2. Integer Programming? (IP) is a mathematical structure leading to a solution as a linear programming tool and providing a substantially faster solution.
3. DBS develops a solution overcoming the LG method's limitations on nested pits by calculating production time, block destination, and production goals and capacities [22].

4.3. Assigning Economic Value to Blocks

Each block in the ore block model performed economic or non-economic value based on the assigned grade. This value is determined by a cut-off in some optimization software, i.e., threshold grade, in some software is determined directly according to the economic value of the block based on its grade (Fig. 1) and its interaction with other blocks. If the block has a value that is sent to the plant after the optimization algorithm operation, it is referred to as an "economic block;" otherwise, it is referred to as a "non-economic block" and will be sent to the waste site.

The economic values of the blocks are defined in two ways, similar to those in Fig. 1 [23]:

1) Economic Value Process: A block is perceived to be economically based on its cost value and sent to the process plant.

$$EVP\left(\$\right) = Ct\cdot\left(SP-SC\right) - Bt\cdot\left(PC+MC\right) \qquad [5]$$

EVP stands for economic value, *Ct* stands for the amount of obtained concentrate, *SP* stands for the sales price, *SC* stands for sales cost, *Bt* stands for block weight, *PC* stands for process cost, and MC stands for mining cost.

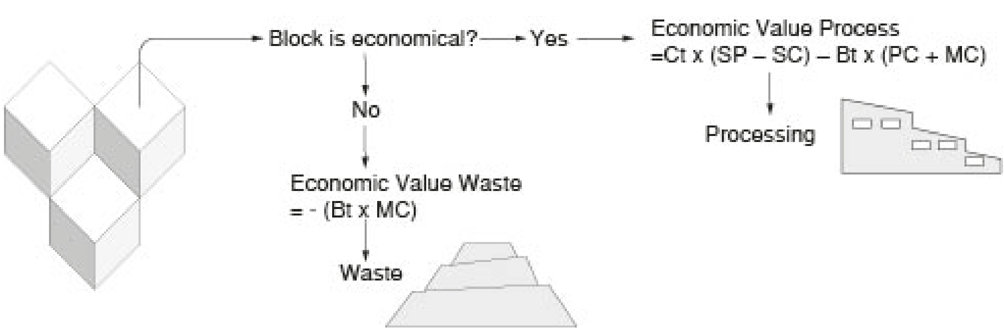


Fig. 1. Block separation in optimization according to economic value

For instance; if a block's grade is 6.00% Cr_2O_3 (at the same time, this is feeding grade for processing plant) then with coefficient 2.107 the tailing grade will be from F/T 2.85% Cr_2O_3. Metallurgical recovery if the concentrate grade is 46% Cr_2O_3 for this block is from equation [3];

$$\%Recovery = \frac{46.00 \times (6.00 - 2.85)}{6.00 \times (46.00 - 2.85)} \times 100 = \%56$$

For a 10 m × 10 m × 10 m size of block and with 2.7 t/m^3 of specific gravity, the amount of concentrate ton (named as Ct for optimization formula) is from equation [4];

$$Ct = \frac{2700 \times 6.00 \times 0.56}{46.00} = 197.24 \ \text{ tons}$$

Economic value for this block for a 227 $/t of the selling price, 20 $/t of selling cost, 2.51 $/t of processing cost, and 2.01 $ of mining cost is from equation [5];

$$EVP = \frac{197.24 \times (227.00 - 20.00)}{2700 \times (2.51 + 2.01)} = 28624 \ \$$$

2) Economic Value Waste: A block is not evaluated as economical in terms of its value and is discharged from the pit to the waste area.

$$EVW\ (\$) = -(Bt \cdot MC) \qquad [6]$$

Here, *EVW* is the economic value of waste.

Because the algorithm can analyze each block separately, this method is more realistic than the conventional one. Nested pits are not required because it optimizes and plans in a single pass to yield the highest NPV in the shortest time.

Based on the system of the LG methodology, blocks are divided to achieve the proposed ore production; however, DBS is more reliable because it aims to extract the complete block only at a certain time. With its ability to put high-quality blocks into production first, DBS can predict the waste involved in accessing blocks with a higher economic value [24]. In summary, it shapes the pit by trying to reach the maximum NPV value for each period in the optimization.

4.4. Application

4.4.1. Case Study Location

The chrome site, which uses application data, is located within the boundaries of Aladağ Township, Adana Province, Turkey. The site covers an area of 1 388 ha and comprises chrome quarries that are operated as large-scale open pits. Low-grade run-of-the-mine chromium ore produced from the site is increased to 46% Cr_2O_3 and above at the concentrate plant at the site. The process is the gravity method for chromite. Material size is reduced and goes to the shaking tables after grinding processes. There are 3 types of material after shaking table; concentrate, middling and, tailing. The concentrate produced is exported to countries, such as China, Japan, and Russia.

4.4.2. Data and Parameter Analysis

The analysis results of 70 samples revealed that daily metallurgical recovery values can reach a maximum of 63%, and Table I summarized the measurement values.

TABLE I

Results of process plant analysis

Sample No.	Feed Grade %	Tailing Grade %	Concentrate Grade %	Recovery %	Feed/Tailing Rate
1	7.34	3.63	46.38	55	2.02
2	7.85	3.39	45.63	61	2.32
3	9.03	4.39	45.23	57	2.06
4	13.10	6.38	47.88	59	2.05
5	7.63	3.66	46.32	56	2.08
6	7.53	3.36	44.56	60	2.24
7	7.50	3.40	44.50	59	2.21
8	7.85	3.62	45.53	59	2.17
65	7.05	3.12	46.15	60	2.26
66	6.24	2.72	45.79	60	2.29
67	7.46	3.60	45.02	56	2.07
68	7.65	3.70	46.97	56	2.07
69	8.70	4.62	47.03	52	1.88
70	8.40	4.20	46.80	55	2.00

Table II shows correlation coefficients indicating the relationship between the parameters. The correlation coefficient between the feed and tailing grades is 0.635, and a negative relationship is observed between the tailing grade and recovery. Furthermore, a positive correlation is noted between the proportion of feed/tailing grade and recovery with the ratio of the established feed to the tailing grade. Table III presents descriptive statistical values of the data.

The grade value is contained in each block (if the block is sent to the plant as the material being fed) is divided by the average value of the Gamma coefficient determined by Fig. 2 to find the tailing grade. Therefore, the grades of all 868 019 blocks (e.g., tailing, waste, and ore) were divided by the value of 2 107, tailing tenors were assigned to the blocks, and their metallurgical

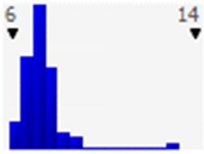
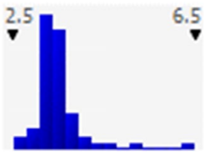
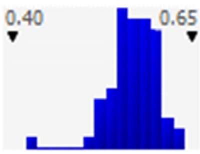
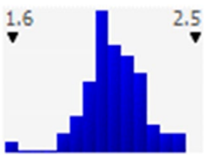
TABLE II

Correlation matrix of analysis results

	Feed	Tailing	Concentrate	Recovery	F/T Rate
Feed	1.000				
Tailing	0.635	1.000			
Concentrate	−0.077	0.044	1.000		
Recovery	0.199	−0.552	−0.173	1.000	
F/T Rate	0.050	−0.681	−0.167	0.968	1.000

TABLE III

Statistical results of sample analyses and distribution charts

Parameter	Distribution Graph	Minimum	Maximum	Mean	St. Dev.	5%	95%	Count
Feed		6.24	13.10	7.56	0.84	6.72	8.69	70.00
Tailing		2.72	6.38	3.61	0.50	3.18	4.39	70.00
Concentrate		42.24	47.88	45.41	1.37	42.90	47.28	70.00
Recovery		0.43	0.63	0.57	0.03	0.53	0.61	70.00
F/T Rate		1.61	2.43	2.11	0.13	1.94	2.32	70.00

recoveries were calculated separately (for each block). In this way, economic values (process and waste) of all blocks are calculated separately according to blocks' grades. All the blocks have 10 m × 10 m × 10 m of dimensions. There are two types of blocks in the block model as one is ore blocks which are inside of the solid ore model and the other one is waste blocks which contain blocks that are out of the solid model. Waste blocks have zero grade in percent.

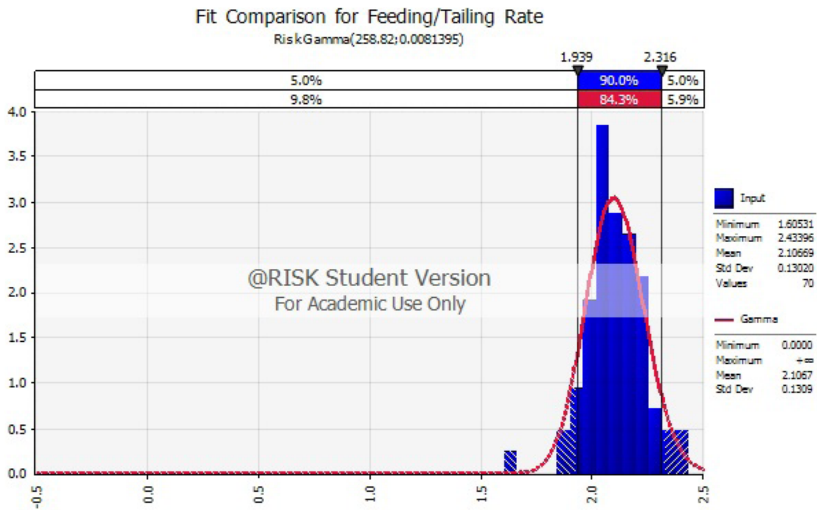


Fig. 2. Feeding/tailing distribution graph

The operational costs were calculated based on an annual production of 1,800,000 tons of run-of-mine ore and 5,200,000 tons of stripping. The process costs were calculated according to the processing of 1,800,000 tons of run-of-the mine chromium ore annually and were summarized in Table IV.

TABLE IV

Open-pit, processing, and sales costs

Cost Unit	Open Pit		Processing		Sales Cost	
	Cost – $	Unit Cost – $/ton	Cost – $	Unit Cost – $/ton	Cost – $	Unit Cost – $/ton
Labour	515 368	0.29	288 158	0.16	—	—
Equipment	2 397 953	1.33	420 074	0.23	—	—
G.P.E*	500 405	0.28	2 308 879	1.28	—	—
Indirect Costs	206 930	0.11	1 492 351	0.84	—	—
Ore Transportation to Port	—	—	—	—	—	9.00
F.O.B. etc.	—	—	—	—	—	9.00
G&A Costs	—	—	—	—	—	2.00
Total	3 620 657	2.01	4 509 462	2.51	—	20.00

* G.P.E.: General production costs (electricity, maintenance-repair, etc.)

4.4.3. Optimization Study

In this study, the economic values of blocks were calculated as ore and waste for each block through Equations [5] and [6]. The blocks with calculated grades, recoveries, block tonnages, and economic values were transferred to SimSched DBS (version 1.0.1) software, and optimizations were performed (Figs 3 and 4).

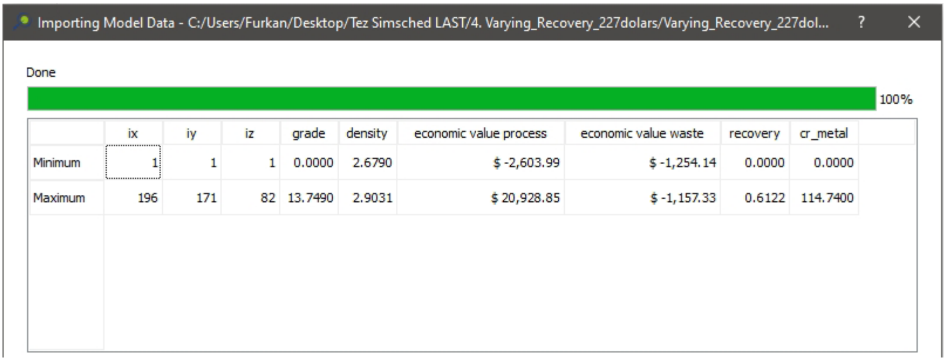


Fig. 3. SimSched DBS data transfer control screen

Fig. 4 shows optimization parameters used for scenarios. In this screen, the Geometric constraints are constraints for the optimization process. Minimum widths (mining) represent working lengths in horizontal so 30 m means that can be maximum of 30 m advance in the pit per period and Minimum widths (bottom) represent working space to work in the pit bottom the during loading and excavating proceses. The vertical rate of advance is a value represent vertical advance in the pit per year as maximum.

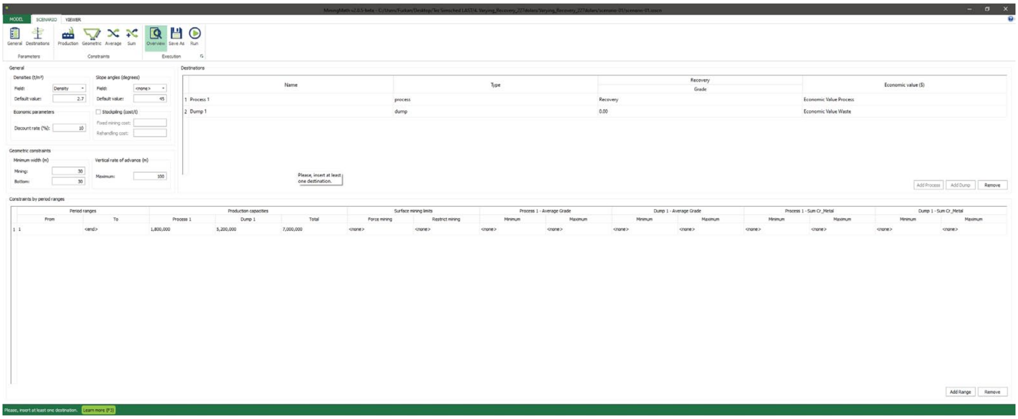


Fig. 4. SimSched DBS optimization screen

4.4.4. Scenarios and Evaluation

Two studies were established with the optimization parameters of the seven scenarios specified in Table V to obtain the optimum pit boundaries required to achieve the maximum NPV as 1) Optimization I (Opt. I): sale price 227 $/ton with fixed metallurgical recovery (60%) and 2) Optimization II (Opt. II): sale price $227/ton with metallurgical recovery varying by block.

Tables V and VI show the optimization parameters and results based on these parameters, and Fig. 5 shows a comparison of these results.

TABLE V

Parameters used in optimization scenarios

Scenarios	DBS Optimization Parameters				
	Discount Rate – %	Slope – degree	Mining Width – m	Bottom Width – m	Vertical Rate of Advance – m
1	10	45	30	30	100
2	10	40	30	30	100
3	10	50	30	30	100
4	10	50	20	40	100
5	10	50	50	30	100
6	10	50	30	30	50
7	10	50	30	30	150

TABLE VI

Optimization output results

Parameters	Scenarios													
	1		2		3		4		5		6		7	
	Opt. I	Opt. II	Opt. I	Opt. II	Opt. I	Opt. II	Opt. I	Opt. II	Opt. I	Opt. II	Opt. I	Opt. II	Opt. I	Opt. II
Production – Mt	6.75	6.24	6.60	6.28	7.60	6.62	6.84	7.15	6.38	6.18	6.67	6.79	7.83	7.86
Waste – Mt	15.68	13.81	17.75	16.49	13.84	13.39	15.74	13.13	16.05	13.83	15.76	13.22	14.61	12.15
NPV –$M	17.80	13.80	14.50	10.50	24.10	16.70	17.60	18.20	16.30	14.00	18.80	19.10	24.00	22.60
Concentrate – kt	420	362	414	368	459	386	422	404	407	368	425	401	462	430
Period	5	4	5	4	5	5	5	5	5	5	5	4	5	5

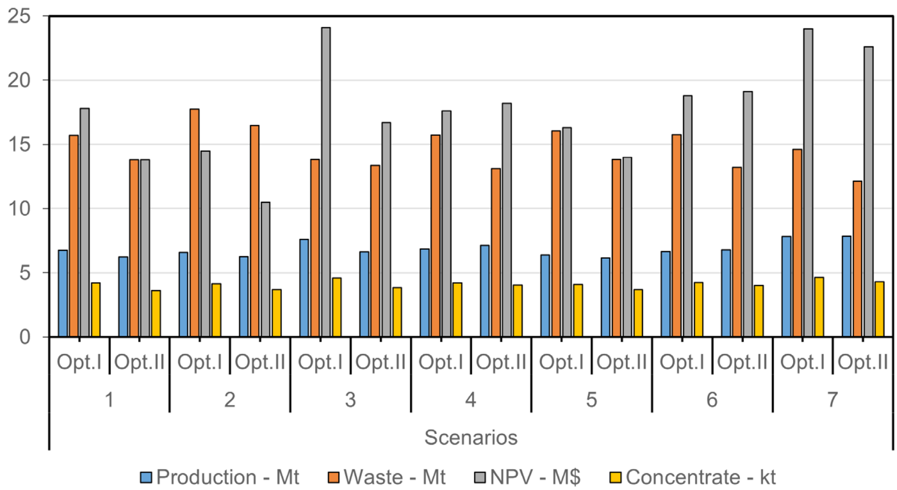


Fig. 5. Chart of comparison of optimization results

The highest NPV was obtained in scenarios with an overall slope angle of 50, whereas increasing the amount of vertical advance increased the NPV (Fig. 6).

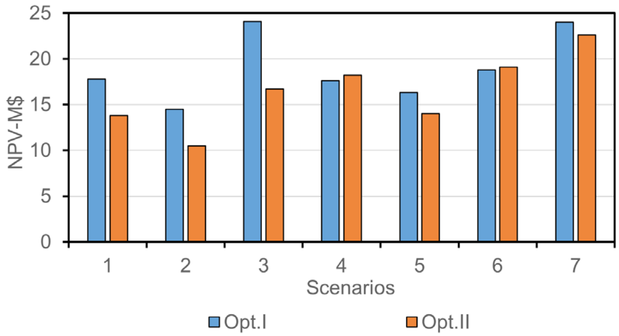


Fig. 6. NPV comparison chart of Optimization I and II scenarios

According to the results (Table VII and Fig. 7), in optimization scenarios with a fixed recovery value, the average grades of the blocks sent to the plant were seen to be lower than those in variable-recovery scenarios because blocks with lower grades are also considered. After all, the fixed recovery value is greater than the variable calculated value.

TABLE VII

Plant feeding tonnages and average grades produced by optimizations

Scenarios	Optimization-I		Optimization-II		Avg. Grade Difference % (Opt. I-Opt. II)
	Feeding – ton	Avg. Grade – %	Feeding – ton	Avg. Grade – %	
1	6 751 170	4.77	6 241 550	4.79	−0.02
2	6 600 360	4.81	6 278 850	4.85	−0.04
3	7 608 820	4.62	6 619 590	4.82	−0.20
4	6 846 160	4.73	7 152 550	4.68	+0.05
5	6 383 890	4.89	6 178 210	4.92	−0.03
6	6 672 220	4.89	6 788 140	4.89	0.00
7	7 829 080	4.53	7 858 930	4.54	−0.01

A significant difference was noted in the NPVs that will be based on the results of optimization studies. Therefore, it was determined that a variable-recovery value that produces close to actual results would be preferable to a fixed recovery value. The NPV difference can reach $7.4 million in Optimization II, scenario number 3. This finding corresponds to a difference of approximately 30% in Optimization I and II. The difference is $1.4 million based on scenario number 7, which has the highest NPV. Based on variable recovery, this corresponds to a difference of approximately 7%. (Fig. 8).

Table VIII compares the Optimization II recovery values with fixed recoveries. In Optimization II scenarios, the maximum average recovery value is 56.28%, and a 3.71% difference is

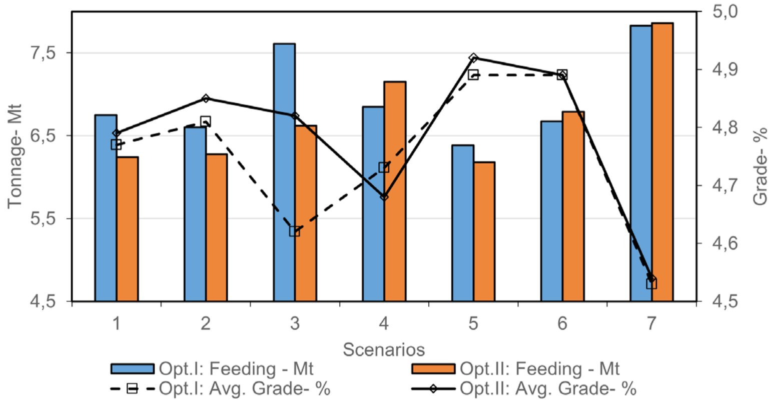


Fig. 7. Comparison of plant feed tonnage and mean grades produced by optimizations

observed when compared with the fixed recovery value of 60% used in Optimization I. When compared with variable-recovery trials, optimization using fixed recovery produced 25 977 tons or 7% more concentrates. Therefore, it should be underlined that this optimization solution on a product basis can be misleading.

TABLE VIII

Comparison of Optimization-II recoveries with fixed recovery

Optimization-II	Minimum	Maximum
Fixed metallurgical recovery – %	60	60
Variable metallurgical recovery – %	54.85	56.28
Recovery difference – %	−5.14	−3.71
Produced concentrate amount by recovery difference – ton	35 980	25 977
Average concentrate amount produced by scenarios – ton	388 452	
Concentrate difference by recovery – %	9%	7%

5. Results/Discussion

Because this study wants to underline that a fixed yield value as a metallurgical yield value from optimization parameters was applied to the blocks, 25,977 tons of concentrated product to be obtained would not have been evaluated within the economy of the quarry. Of course, because this is also a probability, it can be considered results obtained with the best- and worst-case scenarios as offered by many software today. However, the final economic values to be obtained will not correspond with the degree of the economic value to be obtained using variable recovery.

6. Conclusion

In the study on metal production and recovery, solutions were generated by conducting uncertainty-based analyses. A variable-recovery solution scenario offers a realistic optimiza-

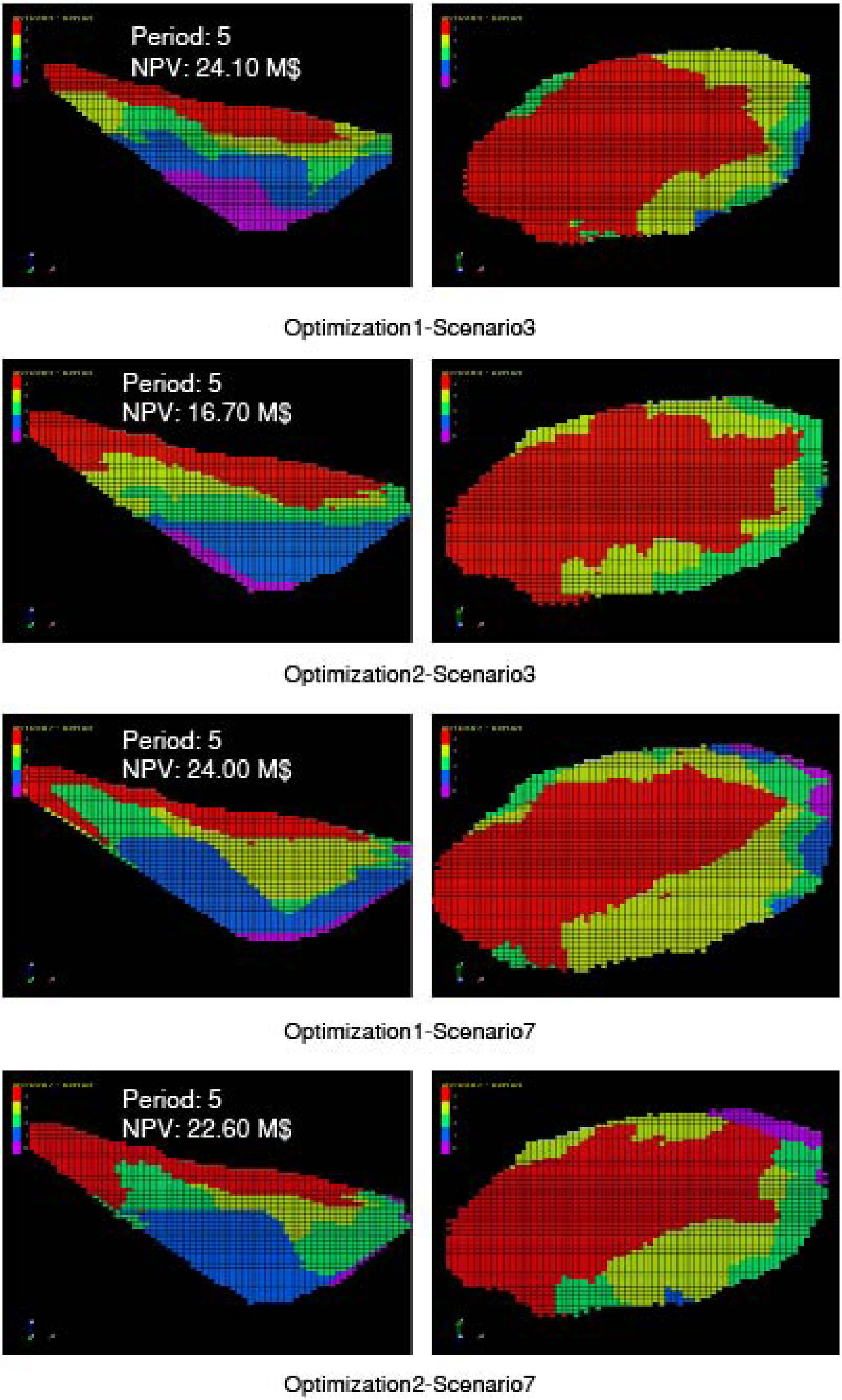


Fig. 8. Image comparison of scenarios 3 and 7 from Optimization I and II

tion scenario providing the maximum NPV for a pit. The results were compared with the fixed recovery solution.

It is believed that in large-scale mines, using variable recovery instead of a fixed recovery parameter throughout the mine life will reveal differences, albeit very small. The approach in the optimization solution to represent the dynamic nature of the site and process has increased the success of calculations. Variable recoveries based on the mineralization analysis results produce effective, successful, and more realistic NPV results than fixed metallurgical recoveries.

Future Scope

With the algorithm or process steps presented in this study, projection parameters, such as the RF, cut-off grade, or metallurgical recovery, which are considered constant will be open to developing among themselves in the future. The F/T ratio will be able to make metallurgical recovery more plausible in all blocks. The limitedness of this method is that computer technology and speed in its application to a large number of blocks to be obtained from larger ores as well as the processing speed for transferring these blocks to the software can be difficult for the user, and the data to be transferred to the software needs to be controlled carefully.

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Author Contributions

Furkan K. Kasa conducted the article study under the supervision of Prof. Ahmet Dağ.

Conflict of Interests

The authors declare that they have no conflict of interest.

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Data Availability Statements

The drilling data was acquired from Dedeman Mining, and they have not been granted their permission for researchers to share their data. Data requests can be made to Dedeman Mining via this email: info@dedemanmining.com.

References

[1] Z. Levinson, R. Dimitrakopoulos, Adaptive simultaneous stochastic optimization of a gold mining complex: A case study. The South Afr. Insitute. Min. Metall. **120**, 221-232 (2015).
DOI: http://dx.doi.org/10.17159/2411-9717/829/2020

[2] G. Bardossy, J. Fodor, Evaluation of Uncertainties and Risks in Geology. Springer-Verlag, Berlin Heidelberg. (2004).

[3] B. Tutmez, An uncertainty oriented fuzzy methodology for grade estimation. Comput. Geosci. **33**, 280-288 (2007). DOI: https://doi.org/10.1016/j.cageo.2006.09.001

[4] B. Groeneveld, E. Lame, Flexible open-pit enamel design under uncertainty. J. Min. Sci. **47**, 212-226 (2011). DOI: https://doi.org/10.1134/S1062739147020080

[5] C. Montoya, X. Emery, E. Rubio, J. Wiertz, Multivariate resource modelling for assessing uncertainty in mine design and mine planning. J. South. Afr. Inst. Min. Metall. **112**, 353-363 (2012).

[6] R.C. Goodfellow, R. Dimitrakopoulos, Global optimization of open-pit mining complexes with uncertainty. Appl. Soft. Comput. **40**, 292-304 (2016). DOI: https://doi.org/10.1016/j.asoc.2015.11.038

[7] J.B. Boisvert, M.E. Rossi, K. Ehrig, C.V. Deutsch, Geometallurgical modeling at Olympic dam mine. South Australia. Math. Geosci. **45**, 901-925 (2013). DOI: https://doi.org/10.1007/s11004-013-9462-5

[8] M. Garrido, J.M. Ortiz, F. Villaseca, W. Kracht, B. Townley, R. Miranda, Change of support using non-additive variables with Gibbs Sampler: application to metallurgical recovery of sulphide ores. Comput. Geosci. **122**, 68-76 (2019). DOI: https://doi.org/10.1016/j.cageo.2018.10.002

[9] L.A. Freire, J.Y.P. Leite, D.N. da Silva, B.G. da Silva, J.C.S. Oliveira, Behavior of the chromite tailings in a centrifugal concentrator (Falcon). REM Int. Eng. J., Ouro. Preto. **72**, 147-152 (2019). DOI: http://doi.org/10.1590/0370-44672018720016

[10] R.G. Dimitrakopoulos, S.A.A. Sabour, Evaluating mine plans under uncertainty: can the real options make a difference? Resour. Policy. **32**, 116-125 (2007). DOI: https://doi.org/10.1016/j.resourpol.2007.06.003

[11] G.L. Smith, S.N. Surujhlal, K.T. Manyuchi, Strategic mine planning - communicating uncertainty with scenarios. J. South Afr. Inst. Min. Metall. **108**, 725-732 (2008).

[12] M. Brunette, Incorporating geo-metallurgical information into mine production scheduling. J Oper. Res. Soc. **62**, 60-68 (2011). DOI: https://doi.org/10.1057/jors.2009.174

[13] M. Brunette, Grade control in multi-variable ore deposits as a quality management problem under uncertainty. Int. J. Qual. Reliab. Managing. **32**, 334-345 (2015). https://doi.org/10.1108/IJQRM-08-2013-0134

[14] E. Moosavi, J. Gholamnejad, Optimal extraction sequence modeling for open pit mining operation considering the dynamic cutoff grade. J. Min. Sci. **52**, 956-964 (2016). DOI: https://doi.org/10.1134/S1062739116041465

[15] L. Montiel, R. Dimitrakopoulos, A heuristic approach to the stochastic optimization of mine production schedules. J. Heuristics. **23**, 397-415 (2017). DOI: https://doi.org/10.1007/s10732-017-9349-6

[16] N. Morales, S. Seguel, A. Cáceres, E. Jélvez, M. Alarcón, Incorporation of geometallurgical attributes and geological uncertainty into long-term open-pit mine planning. Minerals. **9**, 1-26 (2019). DOI: https://doi.org/10.3390/min9020108

[17] D. Kržanović, V. Conić, D. Bugarin, I. Jovanović, D. Božić, Maximizing economic performance in the mining industry by applying bioleaching technology for extraction of polymetallic mineral deposits. Minerals **9**, 1-14 (2019). DOI: https://doi.org/10.3390/min9070400

[18] D.S. Rao, Minerals and Coal Process Calculations. CRC Press, London (2016).

[19] Metso, Basics in Minerals Processing, 11th edn, Metso Corporation, (2018).

[20] N. Morales, E. Jélvez, P. Nancel-Penard, A. Marinho, O. Guimaraes, A comparison of conventional and direct block scheduling methods for open-pit mine production scheduling. In: Proceedings of the 37th APCOM conference, Fairbanks, AK, USA, 23-27 May 2015; Bandopadhyay, Fairbanks, Society for Mining, Metallurgy & Exploration, 1040-1051 (2015).

[21] L. Lerchs, F. Grossman, Optimum design of open-pit mines. Can. Min. Metall. Bull. **58**, 17-24 (1965).

[22] M. Smith, Educational material [Online]. https://drive.google.com/file/d/0ByH6SOBdx3WcMDJrLUl3aC1MbFU/view. Accessed 15 March 2016 (2014).

[23] MiningMath, Tutorial SimSched direct block scheduler beta. https://knowledge.miningmath.com/start-here/economic-values. Accessed 15 December 2021, (2015).

[24] F.R. Souza, H.R. Burgarelli, A.S. Nader, C.E.A. Ortiz, L.S. Chaves, L.A. Carvalho, V.F.N. Torres, T.R. Câmara, R. Galery, Direct block scheduling technology: analysis of Avidity. REM Int. Eng. J. **71**, 97-104 (2018). DOI: http://doi.org/10.1590/0370-44672017710129