Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Mining production planning under mineral price uncertainty: A comparative valuation framework

Parviz Sohrabi
University of Shahrood
Mohammad Ataei
University of Shahrood
Hesam Dehghani
dehghani@hut.ac.ir

Hamedan University of Technology
Zohreh Nabavi
Tarbiat Modares University
Mitra Moghadamfar
Amirkabir University of Technology
Jyrki Savolainen
Lappeenranta-Lahti University of Technology

Research Article

Keywords: Production planning, Angoran mine, Price uncertainty, Monte Carlo simulation

Posted Date: September 15th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10850701/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Mining production planning under mineral price uncertainty: A comparative valuation framework

Abstract

Production planning in surface mines is one of the most complicated operational issues in the design phase. The existence of uncertainty can lead to unfavorable results in the decisions taken by managers and mineral investors. Despite growing adoption of stochastic valuation approaches, comparative assessment of three distinct approaches including simulation-based decision-making system, @Risk Monte Carlo simulation, and NPV Scheduler optimization, applied to the same ore body under consistent price-uncertainty assumptions remains limited. In this article, production planning of the Angoran Pb-Zn open-pit mine is evaluated using three uncertainty-quantification methods, each applied to five annual-production-rate scenarios (0.5-1.2 Mt/yr). NPV Scheduler results range from $5,720 M to $8,489 M. The MCS-based method yields NPV estimates approximately 15-20% higher than the NPV baseline, due to its incorporation of a 4% per year price drift over the mine life. All three methods confirm the 1.2 Mt/yr scenario as NPV-maximising. This comparison is intended to illustrate how different uncertainty-quantification approaches influence production-scenario selection, rather than to identify a single universally superior valuation method.

Keywords: Production planning, Angoran mine, Price uncertainty, Monte Carlo simulation

1. Introduction

In modern mining, the economic parameters governing cost and productivity have always been central to investment decisions. Reducing the extraction costs and increasing throughput within a fixed timeframe are the primary levers for improve increase profitability. Production planning is therefore a critical component of mine management (Ataei and Osanloo, 2003). Mining projects are typically capital-intensive, with long economic lives. The economic viability of mining investments is more dependent on the uncertain development of metal prices in the world market and how the specific risk of the project is realized. Mineral investments are substantial capital commitment and are valued taking into account the uncertainties that surround them, including the real options that may be found associated with these investments (Collan, 2011). Most mining project evaluations focus on quantitative investment analysis based on mining industry surveys, valuation methods are based around discounted cash flow (DCF) metrics such as net present value (NPV), internal rate of return, and payback period (Bhappu and Guzman, 1995). For all the methods used in project production planning, screening analysis based on DCF is a practical threshold that every project must be performed before any analysis (Smith, 2002).

1.1 Literature review

Currently, production planning in mining has become an important issue due to the many uncertainties that exist in the production and processing cycle of minerals, and many studies have addressed this field with different methods. Uncertainty quantification in mine planning has attracted significant attention over recent decades, spanning three broad domains: geological and grade uncertainty (Lagos et al., 2022; Nabavi et al., 2024; Rimélé et al., 2020), operational and technical uncertainty (Jiang and Dimitrakopoulos, 2024; Mirzehi et al., 2023; Quigley and Dimitrakopoulos, 2020; Upadhyay and

Askari-Nasab, 2018), and economic and market uncertainty (Dehghani et al., 2024; Salehi et al., 2025; Saliba and Dimitrakopoulos, 2019).

In terms of economic and market uncertainty, Samala et al. (2022) used widely adopted performance metrics including interest rate, dwell time, system utilization, and availability, as surrogate indicators for diagnosing production system disturbances in real-time, and considered four different configurations as criteria for an MCDM-TOPSIS-based simulation approach. Fan et al. (2023) showed that under a cap-and-trade policy, with the uncertainty of the future emission price, the firm can flexibly adjust its production quantity to increase its profit and find low incentives to invest in clean technology. Li and Maréchal (2023) proposed a systematic method for exploring the uncertainty space, combining mixed integer linear programming (MILP), MCS, and machine learning to quantify the effects of uncertainty on an energy system at the national, regional, and global levels, as demonstrated in a local case study. Tolouei and Moosavi (2023)in a study using LTPSOP hybrid model and accounting for production scheduling uncertainty by combining Augmented Lagrangian Relaxation (ALR) and the Human Mindful Search (HMS) meta-heuristic algorithm, found that the project's NPV improved by 18.63% compared to the base case. Jiu et al. (2023) developed a two-stage approach based on robust optimization to adapt the production rate using a linear decision rule, demonstrating long-term cost savings.

Recently, Mirzehi and Afrapoli (2024a, 2024b) incorporated carbon price uncertainty into long term mine planning through an integrated LCA-MILP framework, demonstrating that economic and environmental objectives can be concurrently optimized without severe financial penalty. Madziwa et al. (2026) integrated commodity price volatility into the Lerchs-Grossmann algorithm by forecasting gold prices using an Autoregressive Distributed Lag (ARDL) model, demonstrating that a constant-price assumption underestimates NPV by approximately 35% during rising markets and overestimates it by nearly 30% during declining markets.

Furthermore, price forecasting lies at the heart of economic uncertainty quantification in mine planning and has been a central focus research in recent years, Kahraman and Akay (2022); Sorabi et al. (2023); Tsoulos and Charilogis (2023); Xu and Zhang (2022) each applied distinct forecasting approaches to mineral commodities, demonstrating improved prediction accuracy relative to conventional methods.

1.2 Research gaps and contributions

While the studies reviewed above demonstrate the value of stochastic optimization, machine-learning-based forecasting, and multi-criteria decision frameworks individually, few directly compare how different uncertainty-quantification techniques from simplified stochastic NPV models to commercial mine-scheduling software affect the choice of annual production rate for the same orebody. This study addresses that gap by applying three such approaches to a single case study (the Angoran Pb-Zn deposit) under a common set of production-rate scenarios.

It is important to note that the three methods compared in this study address commodity price uncertainty in fundamentally different ways: the NPV Scheduler approach uses a fixed historical mean price and produces a single deterministic NPV; the @Risk Monte Carlo method generates a probability distribution of NPV outcomes by sampling from a fitted price-return distribution; and the simulation-based decision system uses stochastic price vectors to rank alternative mine plans by expected NPV. Because these methods have different scopes, the comparison presented here is best understood as an illustration of how

each approach frames the same decision problem, rather than a head-to-head performance test. The consistent rank-ordering of production-rate scenarios across all three methods is the primary finding of practical relevance.

The principal contributions of this study are as follows: (1) Systematic comparative framework. This paper applies three fundamentally distinct uncertainty-quantification approaches including a simulation-based decision-making system, @Risk-MCS, and deterministic NPV Scheduler optimization, applied to exactly the same open-pit mine block model, mine design, and scenario set, enabling a like-for-like comparison of their outputs and decision implications; (2) By incorporating LME monthly settlement data from January 2005 through June 2026 (258 months), the study updates the statistical parameters (mean price, drift, volatility) used in all three models to reflect post-pandemic price cycles, reducing the risk of parameter bias from a short data window; (3) As a practical production-rate guidance, five production-rate scenarios (0.5–1.2 Mt/yr) are evaluated across all three models, providing mine planners and investors with a consistent, scenario-by-scenario economic picture; (4) By using a method-comparison transparency, the paper demonstrates that the choice of uncertainty-quantification approach materially influences the absolute NPV estimate while leaving the rank-ordering of production-rate scenarios unchanged, a finding of direct practical relevance to method selection in early-stage mine planning.

2. Methods and materials

2.1. Simulation-based decision-making system for optimal mine production plan selection

Combining the use of the available capabilities of block sequence software and statistical modeling of metal prices, and finally the mining plan will be selected using a management decision system. The case study is evaluated in two stages. In the first step, a set of alternative mining plans is extracted from the mine planning software, and secondly, the economic returns of the expected range for each mining plan are modeled by stochastic MCS using different statistical price SDE models. In this method, we will not only consider the initial price of the metal, but we will also apply it to the effects of price fluctuations and trends.

2.1.1 Using historical data to model metal prices

Historical metal price data serves as a broad indicator of future price behavior. To advance this research, the monthly price data of lead and zinc from January 2005 to June 2026 were obtained at www.investing.com. It is assumed that the price uncertainty is parametric. Therefore, historical data serves as a basis for price prediction. In this case, the mean price value, p (Eq. 1), and the annual volatility, σ_p (Eq. 2), were fitted to historical monthly price data as (Savolainen et al., 2022):

$$\bar{p} = \frac{1}{n}\sum_{i=1}^{p} p_i \tag{1}$$

$$\sigma_p = \sqrt{12} * \sqrt{\frac{1}{1+n}\sum_{i=1}^{n}(p_i - \bar{p})^2} \tag{2}$$

By fitting a straight line on the resulting graph, Eq. 3 can be obtained as:

$$y = \left(k_p * x\right) + b \tag{3}$$

Where y is the linear trend of x, which is a time variable, and k_p is the rate of change per unit of time. b is the initial value of the function trend. In this research, to obtain the annual change, we multiply the monthly OLS slope by 12 and divide by mean price of the period.

$$d_p = \frac{12k_p}{\bar{p}_{i\ldots j}} \quad \forall i\,, j \in [1, N] \wedge j{>}i \tag{4}$$

Using Eq. 1 to 4, the fitting results of zinc price are shown in Fig. 1. As shown in Fig. 1, in the short to medium term, volatility and rate drift are highly dependent on the time frame chosen. The scenario volatility values of 3% and 9% per year are derived from the short-window (24–48 month) sub-period volatility estimates shown in Fig. 1B, which representa the minimum and upper-medium range of observed rolling volatility for the Zn price series. The long-run annual volatility over the full 2005-2026 window is approximately 26%, indicating that the scenario bounds are conservative and that actual NPV distributions may be substantially wider than those shown in Fig. 8, which is acknowledged as a limitation.

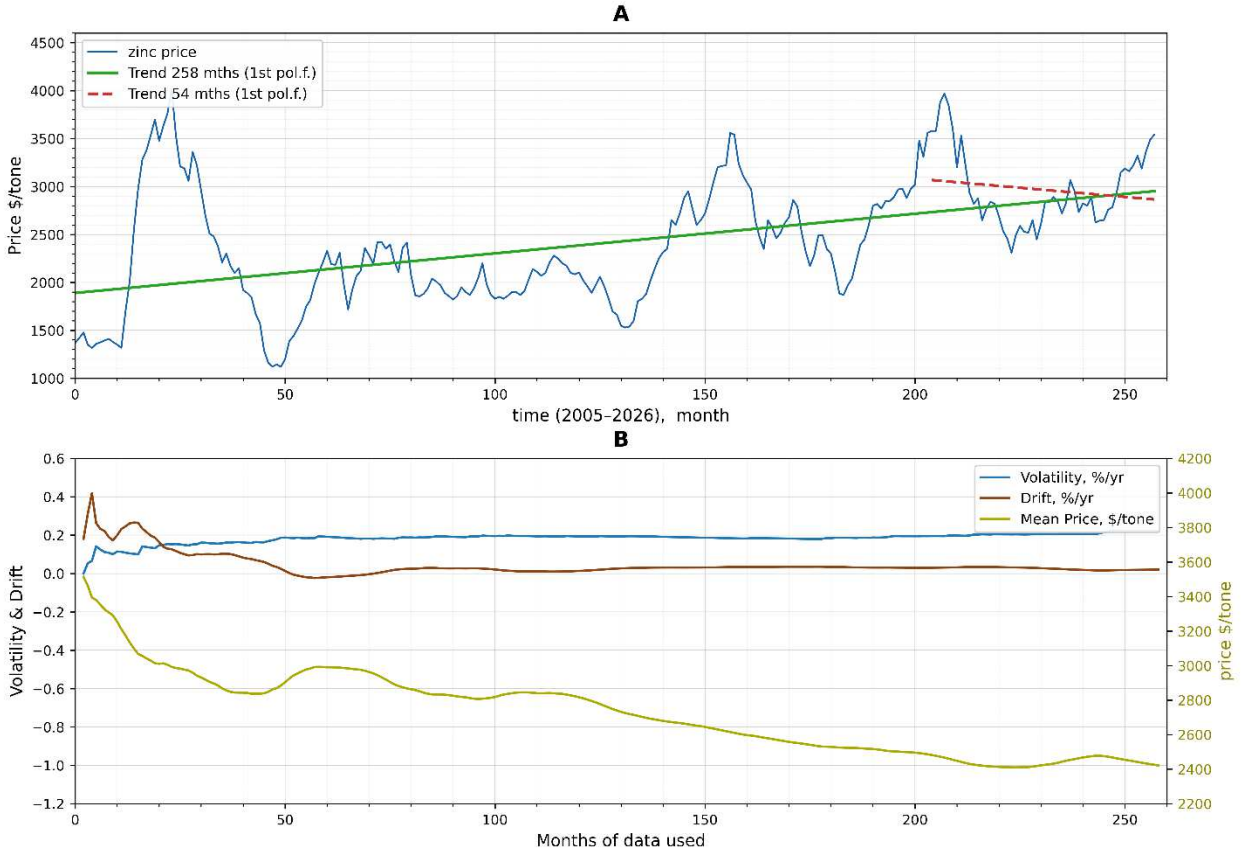


Fig. 1 A: The price of zinc from 2005 to 2026 is plotted with two linear trends. B: Fitting the parameters of the zinc price as a function of month for analysis.

2.1.2 Simulation to choose the optimal mining plan

The project's NPV is an estimate of the value of future cash flows based on today's money such that the more distant the cash flows are, the more uncertain they are, which is accounted for by a discount factor. Here, NPV can be written as Eq. 5:

$$NPV = (\sum_{i=1}^{n} (R_t - C_t)/df_t) - I_0 \quad (5)$$

Where R_t is the revenue in month t (dependent on price, p), C_t is the cost including taxes for month t, df_t is the discount factor in month t and I_0 is the initial investment at t = 0. In the present study, C_t encompasses direct mining costs ($3/t ore) and processing and smelting costs ($6.5/t ore) as given in Table 1. Royalties and corporate income tax are not separately modelled; NPV values reported throughout this study are therefore on a pre-tax basis.

A simple NPV model was created in MATLAB programming software so that it can be created with price vectors. In this model, the price vector is taken as an input by the software to enable the flexible execution of Monte Carlo random simulation (MCS) to run the model. In this study, MCS is run for each scenario using a set of 1000 zinc price realizations for each price parameter. It also provides a comparison of the performance of different alternative mining scenarios for each of the given vectors: a numerical ranking from 1(highest NPV) to 5 (lowest) is assigned to each scenarios (see Fig. 2) (Savolainen et al., 2022).

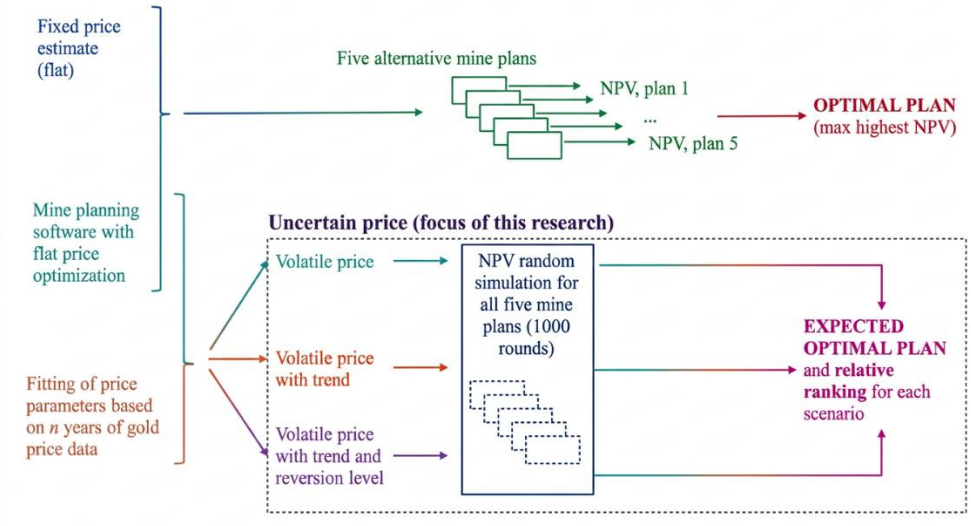


Fig.2 Schematic illustration of the simulation and analysis process.

Stochastic simulations are tested for five alternative mine designs. The process can be summarized as follows:

a. First, by creating "n" alternative mine scenarios using mine planning software, based on similar pit designs but with different mill throughput, processing plant scale, and capital costs.

b. Conduct price uncertainty sensitivity analysis for each of the scenarios included in the NPV simulation to evaluate the relative goodness of the alternative scenarios. Each of the parameters of starting prices, volatility and returns are different in sensitivity analysis.

A conceptual information system then automatically takes a management-estimated price vector (with uncertainty bounds included) and matches it to the best fit of the mine plan. Ideally, a stochastic price trend analysis using an NPV calculation should be performed for all available mine planning scenarios before deciding on the scope and design of operations. To perform this type of analysis, First, a managerial price estimate input to the simulation system should be created with three values of the best estimate, the lower limit and the upper limit, then the price fluctuation parameter should be calculated based on the best estimate using Eq. 3 and the random price simulation should be executed in a loop and While we examine the scenarios that are above or below the given limits at any point in time in the simulated time interval and iterate until we reach a desired random price value (say 1000) within the given limits then Use it from the set of random price realizations obtained, to run MCS to calculate NPV, and finally we will describe the extraction sequence based on the relative ranking of the plans.

2.2. Price estimation with @Risk software and project evaluation with MCS method

The Monte Carlo method is one of the most common techniques used to analyze economic problems. Among the advantages of this method is its straightforward application, because when several uncertain parameters are combined, their evaluation will be very difficult. However, the Monte Carlo method, it is easy to estimate non-deterministic parameters (Ataei et al., 2013). Determining the uncertainties in the Monte Carlo method is done using @Risk software. The price of the mineral is estimated based on their historical data. By using the historical Zinc prices shown in Fig.1A and by @Risk software, its changes are obtained as a fitted function in Fig. 3. The best fitted function in the Monte Carlo method is the Logistic function, whose specifications are shown in Fig. 3 (Dehghani & Ataee-Pour, 2012; Sohrabi et al., 2021).

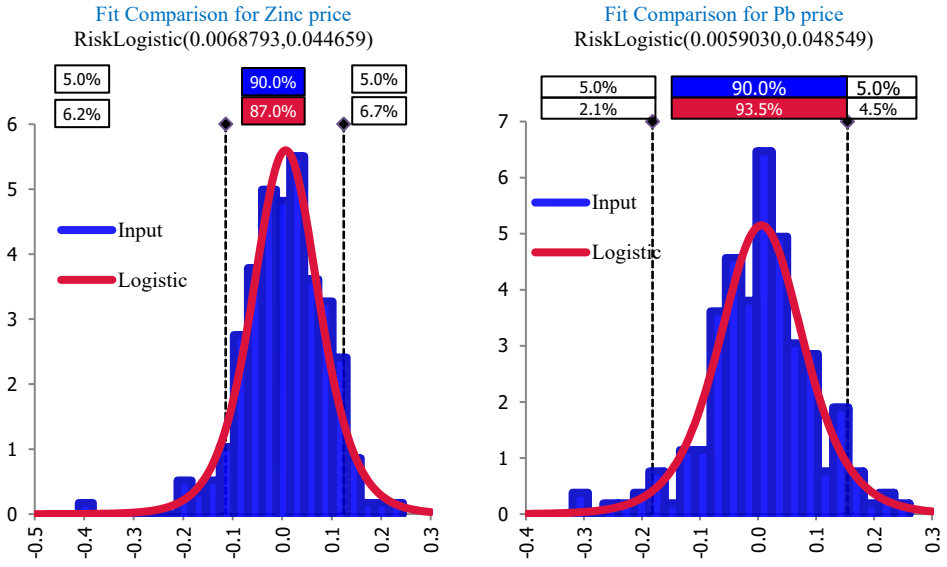


Fig.3 Histogram of the best function of zinc and lead price changes from 2005 to 2022

Finally, assuming the uncertainty of the price during the life of the project, the value of NPV is calculated using @ RISK software.

2.3. Project evaluation with software NPV Scheduler

In this scenario, first the block model of the data related to the exploratory drill hole is created in the Data mine software, and then the NPV value will be calculated with the NPV Scheduler software.

After the information required calculating the value of the blocks is defined in the NPV Scheduler software, this software will calculate the economic model. After determining the final range, the software has a step to determine pushbacks and their number. Pushbacks are created with the aim of dividing the final area into smaller pits that have a more suitable implementation aspect. After determining the number of pushbacks, production planning is defined by defining constraints related to time and extraction tonnage (mineral, tailings or whole extracted rock) and other necessary adjustments will be made depending on the study and design requirements. Therefore, determining the final limit of the mine with the NPV Scheduler software will lead to the results provided by this software (Hajarian et al., 2011).

3. Case Study

Angoran open pit lead and zinc mine is located in Zanjan province (Iran), 136 km southwest of Zanjan city (Fig. 4). This mine is located at 36 degrees and 42 minutes north and 48 degrees and 48 minutes east (Parizanganeh et al., 2010). This mine has a reserve of about 13 million tons of ore. This mine is one of the richest lead and zinc mines in the Middle East. The frequency distribution diagram of lead and zinc grades in Angoran mine is shown in Fig 5. The data related to this mine are shown in Table 1.

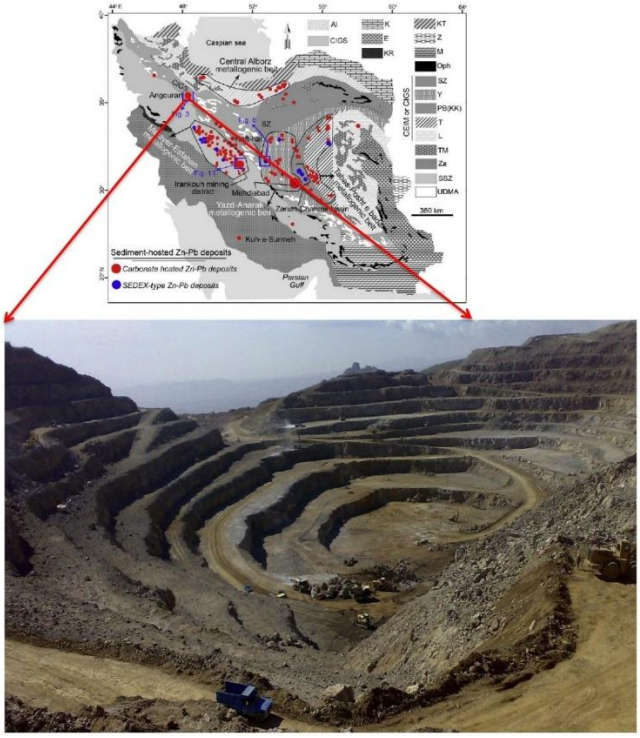


Fig. 4 Angoran Lead and Zinc Mine.

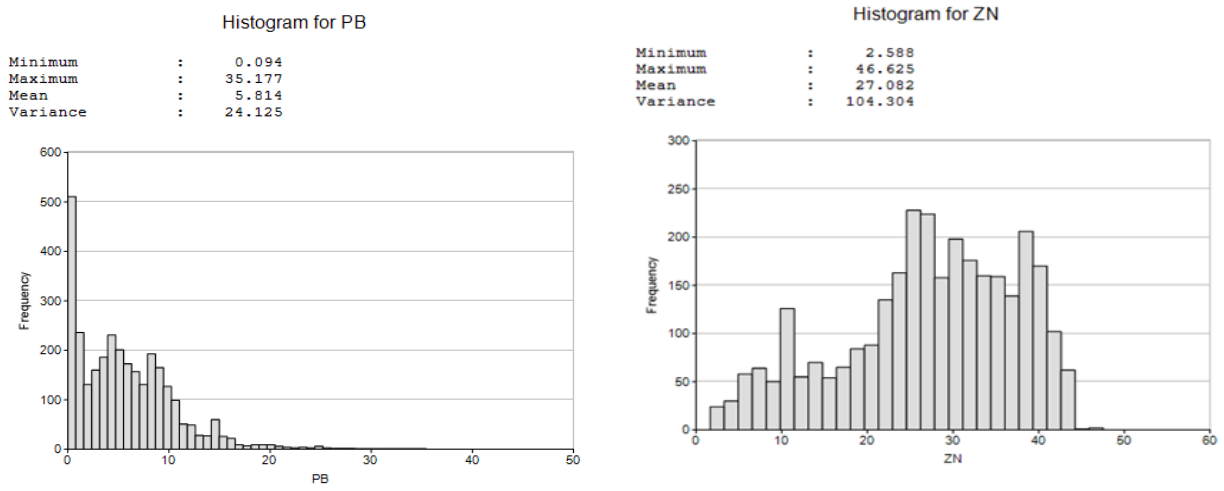


Fig. 5 Distribution diagram of lead and zinc abundance in Angoran mine

Table 1. Angoran Mine specifications

Input data	Amount	unit
Reserve	12,911	M tone
Zinc Average grade	27.082	percentage
Lead Average grade	5.814	percentage
OSR	2.83	-
Zinc price	4054	$/tone
Lead price	2260	$/tone
Capital costs	210	M$
Mining costs	3	$/tone
Processing and melting cost	6.5	$/tone
Recovery	75	percentage
Discount rate	7	percentage

A nominal discount rate of 7% per year is applied in all scenarios, consistent with rates used in prior mineral investment feasibility studies. This rate is used here as a benchmark to enable comparison across methods.

4. Results on project valuation

In order to implement and evaluate the three models that were defined, five scenarios for different production rates are considered. These 5 scenarios include annual production rates of 0.5, 0.7, 0.9, 1 and 1.2 million tons, based on which the life of the mine will be estimated. Therefore, in each of the 3 models that were introduced, 5 scenarios will be analyzed. Before implementing the three models, the economic feasibility of each scenario is first assessed using a long-term average price approach (Dehghani & Ataee-Pour, 2012). In other words, in this case, the prices are considered definite and none of the factors related to volatility, drift, etc. will be taken into account, and its basis is the classic Table DCF. The results related to this section are shown in Table 2.

Table 2. Key parameters of mine planning scenarios

Scenario	0.5 Mt	0.7 Mt	0.9 Mt	1 Mt	1.2 Mt
Life of mine (year)	26	19	15	13	11
Ore milled (Mt/year)	0.5	0.7	0.9	1	1.2
Waste mined (Mt/year)	1.415	1.981	2.547	2.83	3.396

Zinc recovered(tone/year)	143,962	202,325	259,932	287,924	346,576
Lead recovered(tone/year)	36,771	51,678	66,392	73,542	88,523
Initial investment(M$)	150	210	270	300	360
NPV(M$)	5,720.44	6,922.87	7,697.31	7,999.33	8,489.01

Then calculate the price range with the range of all data from 1 to 258 months and calculate the NPV for each mining planning scenario at all points and the results will be as shown in Fig. 6. The sensitivity analysis of all prices is shown on the right side of the image. By deciding on the mining plan, it can be concluded that the biggest NPV will belong to the 1.2 million tons per year mining plan.

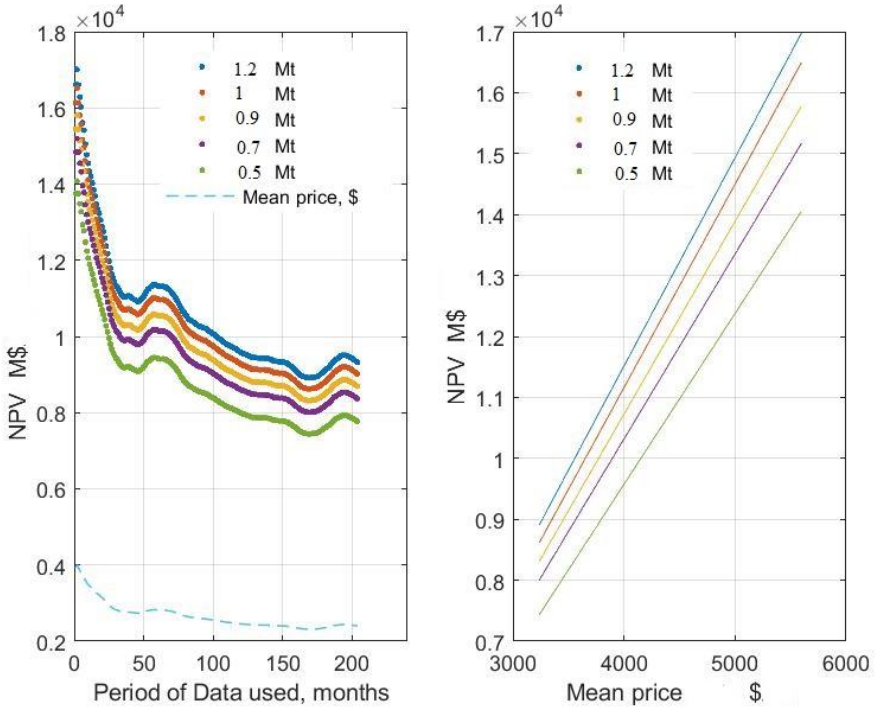


Fig. 6 NPVs of different mine plans using flat, long-term mean price assumption without uncertainty. Left: Project value (M $; dotted lines) as a function of data length (months) taken into account when calculating the historical average price ($; dashed line). Right: Sensitivity analysis of the observed mean price range

4.1. Simulation-based decision-making system for optimal mine production plan selection

As explained earlier, one of the models used for simulation is the model developed by Savolainen and her colleagues in the 2022 project entitled "Simulation based on the decision-making model for choosing the optimal mine plan".(Savolainen et al., 2022).

In the basic analysis with price uncertainty, it is assumed that the price data has a trend (drift = 4% per year), which will be the development of the price using the basic parameters of the price, trend and volatility. The main idea of the mining plan decision system was that three price estimation vectors are needed, two of which serve as minimum and maximum scenarios for each year. The fluctuation parameter is fitted by equation 3 in the minimum to maximum range. Then the relative ranking system of the plans is obtained based on the average NPV. The results of this analysis show that scenarios with a higher production rate have higher NPV than scenarios with a lower production rate. To illustrate these specific price developments, the rank one price vectors for the 1.2 million ton scenario are shown in Fig.7. The

left chart shows the zinc price results starting at $4,054 and the right chart shows the lead price results starting at $2,065. Y-axis shows NPV and X-axis shows the number of years of life of mine (LOM).

Finally, for each of the five defined scenarios, the NPV value has been calculated using 1000 alternative price scenarios applying the current price and with volatility of 3% and 9%. The results are shown in the cumulative NPV histogram in Fig. 8.

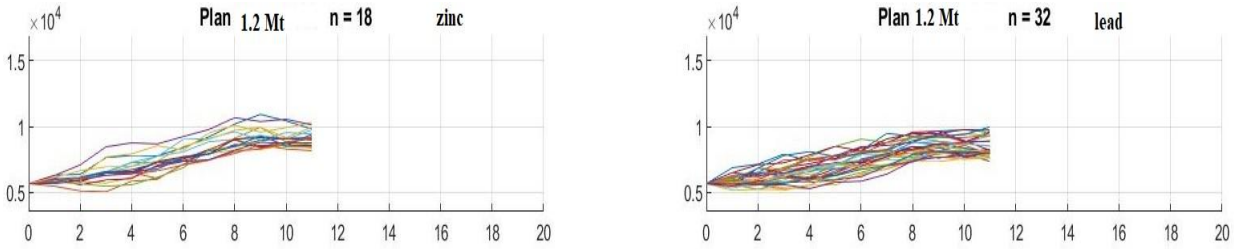


Fig.7. Price vectors extracted from simulation results (n number of allocated vectors)

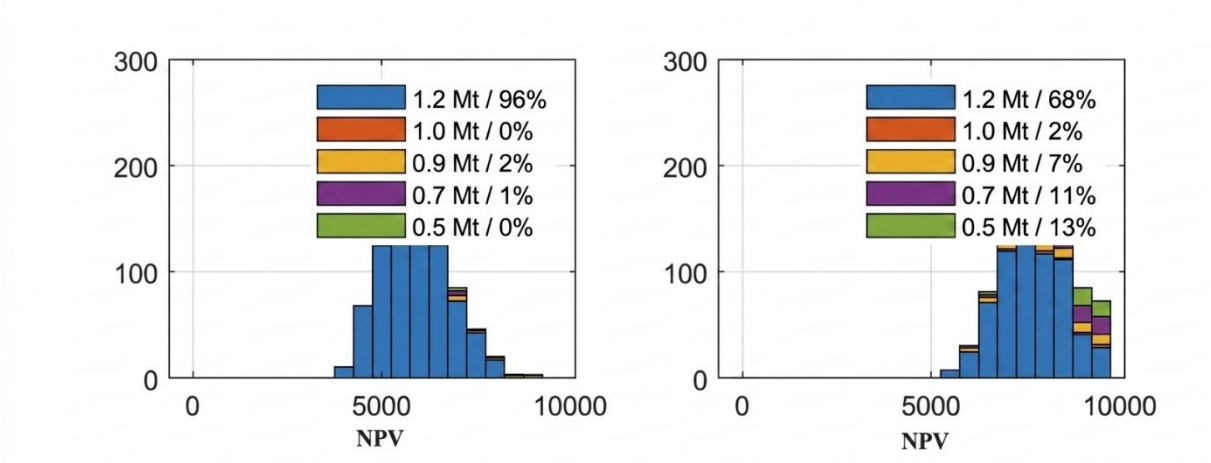


Fig.8. Comparison of cumulative final NPV histograms (Left 3% and right 9% , drift = 4% per year)

As anticipated, the average NPV of different mine planning scenarios with volatility of 3 and 9 percent is almost unchanged. Also, the distribution of NPV for high volatility versus low volatility prices is skewed. Furthermore, in the high volatility scenario, the NPV distributions are right-skewed, because higher price levels generate proportionally larger absolute gains than equivalent price declines generate losses.

4.2. Price estimation with @Risk software and project evaluation with MCS method

Determining the uncertainties in the Monte Carlo method is done using @Risk software. The price of the mineral is estimated based on their historical data. Using the historical prices of lead and zinc, the best fitted function in the Monte Carlo method is the Logistic function, the specifications of which are shown in Fig 3. In this simulation, 5 defined scenarios that include different production rates are performed without applying any trends and volatility in @Risk software. The simulation results of 5 defined scenarios are shown in Fig.9 and 10.

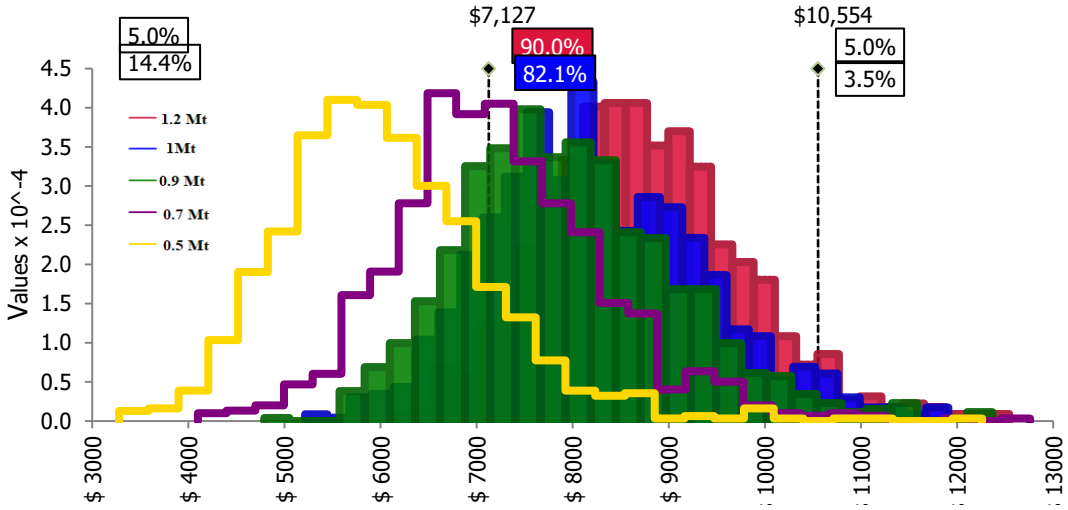


Fig. 9. Cumulative NPV histogram of 5 scenarios

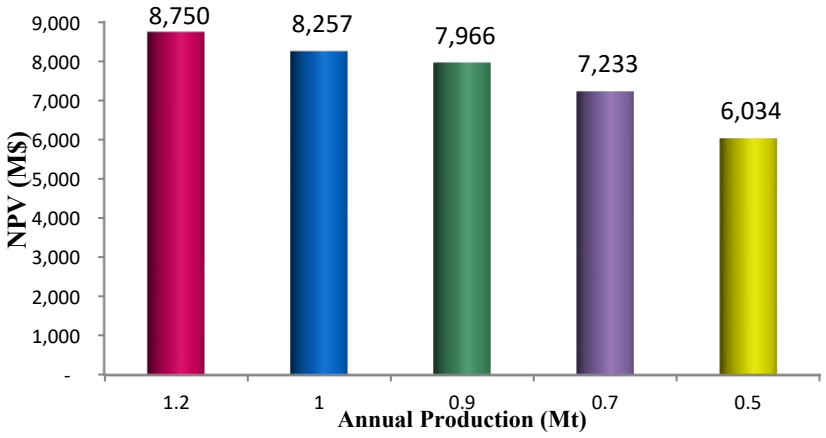


Fig. 10. Monte Carlo simulation results

4.3 Project evaluation with software NPV Scheduler

After determining the final open pit of NPV Scheduler software, mine production planning was done based on 5 defined scenarios. To perform this operation, after determining the final range using the software, pushbacks and their number were designed.

After determining the number of pushbacks, the production planning was done by defining constraints related to time and extraction tonnage (mineral, tailings or whole extracted rock). After determining the NPV value of each of the pushbacks, the range with the highest current net value was selected as the optimal pit. Results related to the different scenarios defined are shown in Figure 11.

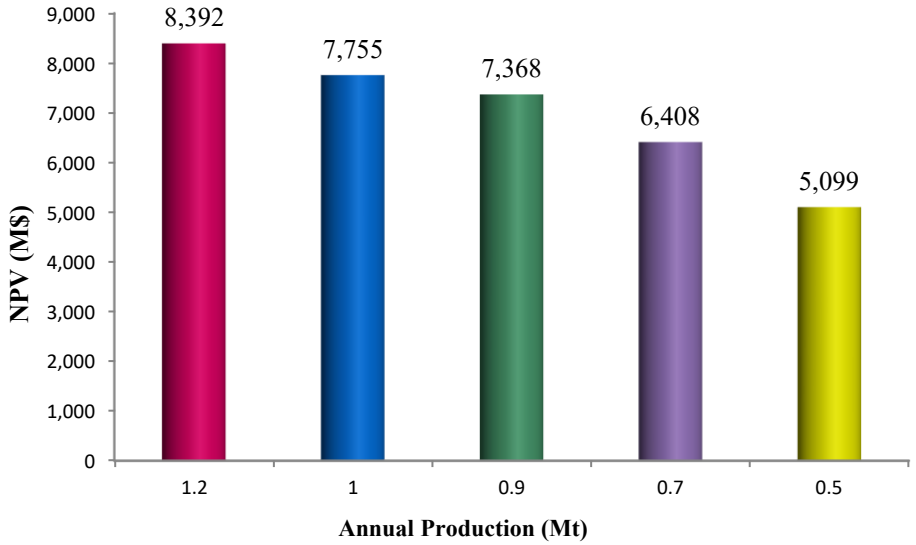


Fig. 11. NPV Scheduler results

4.4 Validation of scenarios

Three methods of evaluating production planning in the mine that were defined in this research were evaluated. As a result of the evaluation of the presented methods, 5 scenarios related to the annual production rate were simulated, the results of which are shown in Fig. 12. As shown in Fig. 12, the results related to the evaluation method with NPV software have the lowest amount of net present value. The reason for minimizing the results of this method is its evaluation using real data. The data used in this method is the same data of exploratory boreholes, which is used to build the block model of the deposit and is used as an input model in the NPV Scheduler software. Another weakness of this method and the classic DCF method is that price uncertainty is not explicitly modelled in either method.

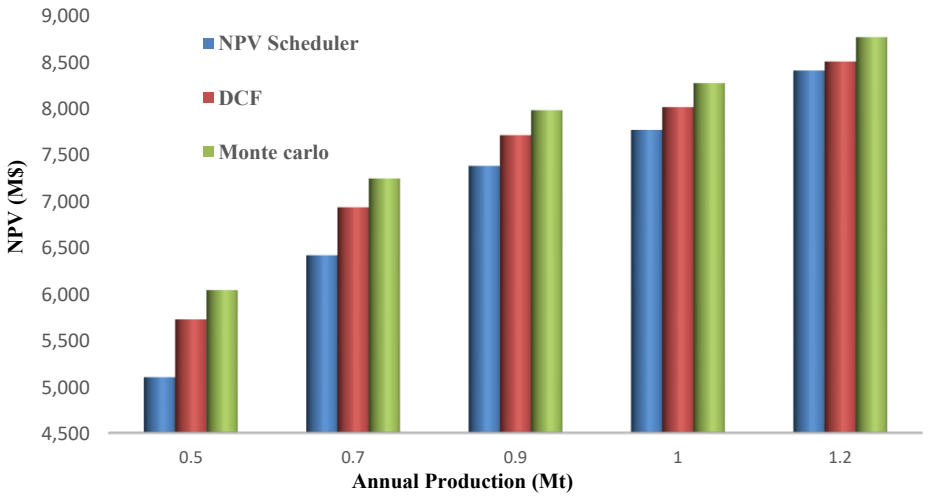


Fig. 12. Comparison chart of 3 methods evaluated in this research

The highest NPV values correspond to the Monte Carlo method. One of the reasons is to control sudden price prediction with the Monte Carlo method. As shown in Fig. 3, the functions used in the Monte Carlo method do this well. One of these functions is Risk Logistic. A regular trend among the three methods studied in all scenarios can be seen in Fig. 12. This shows the detailed investigation in this research and its reliable results.

5. Discussion, Limitations, and Future Work

5.1 Discussion

The results confirm that, for the Angoran Pb-Zn open-pit mine, the rank-ordering of production-rate scenarios is robust across all three valuation methods: the 1.2 Mt/yr scenario consistently yields the highest NPV regardless of the uncertainty-quantification approach used. This stability arises because the dominant driver of NPV is the ratio of annual cash flow to discounted capital cost, which is insensitive to the specific price model when a single discount rate and single price trajectory are applied.

The absolute NPV values differ substantially between methods. The simulation-based decision-making system and @Risk Monte Carlo method incorporate a price drift of 4% per year compounded over mine life. Over a 26-year life (0.5 Mt/yr scenario), this drift compounds to a cumulative price multiplier of approximately 2.77, inflating NPV estimates relative to NPV Scheduler which uses a flat historical mean price. This is not a weakness of the stochastic methods but a difference in scope: they model expected price trajectories, while NPV Scheduler provides a conservative single-point valuation.

The convergence of NPV rankings across methods provides mine planners with a practically useful finding: even under significant price uncertainty, the production-rate decision is relatively insensitive to the choice of valuation model. This supports the use of simpler deterministic models (NPV Scheduler) for early-stage screening, while reserving stochastic approaches for investment-grade feasibility work.

5.2 Limitations and future work

This study models uncertainty in commodity prices only. Ore-grade uncertainty, metallurgical-recovery uncertainty, operating-cost escalation, and foreign-exchange risk all contribute materially to NPV variance. For the Angoran deposit, Zn grades range from 2.6% to 46.6% (Fig. 5), suggesting significant grade variability. A single 7% discount rate does not reflect the specific risk profile of a mining project, which is subject to country risk, currency inconvertibility risk, and regulatory uncertainty. The stripping ratio of 2.83 is applied uniformly across all production rates and the full mine life. In practice, the stripping ratio varies by pushback and sequence, which may underestimate early-year costs in higher-rate scenarios.

Future work should incorporate joint grade-price uncertainty using geostatistical simulation approaches. The GBM assumption should be supplemented with a two-factor model that

separates short-term shocks from long-term equilibrium reversion. Incorporating the prevailing royalty rate, corporate income tax, and profit-sharing arrangements would substantially affect NPV and is essential for an investment-grade assessment. Future work should derive the 3% and 9% bounds from the full empirical return distribution and test NPV ranking sensitivity. Such analysis would clarify the robustness of the production-rate recommendations under more realistic volatility conditions.

6. Conclusions

Economic uncertainty is a central challenge in mining project evaluation, directly affecting investment decisions by shareholders, managers, and engineers. Classical DCF evaluation, long applied to mining projects, has been shown to understate project value when uncertainty is excluded, making informed investment decisions difficult without explicit uncertainty modelling. The purpose of this research is to advance and compare the methods presented in mine planning in recent years, considering the uncertainties. For this reason, in this research, various models were implemented to evaluate the Angoran lead and zinc mine project. The results of the evaluation of these methods are as follows:

- Among the three valuation approaches compared, the Monte Carlo simulation using vector-based price estimation produced the highest NPV across all five production-rate scenarios, reflecting its explicit treatment of price trend and volatility.
- The NPV Scheduler approach, which relies on a fixed current LME price and a block model built from real exploration drilling, produced the lowest NPV values, illustrating the effect of excluding price uncertainty from the valuation.
- Across all three methods, NPV increased monotonically with annual production rate, with the 1.2 Mt/yr scenario yielding the highest NPV and the 0.5 Mt/yr scenario yielding the lowest.

The simulation-based vector method is recommended for investment-grade feasibility studies with mine lives exceeding 10 years, where price drift materially compounds. For rapid screening or mines with short lives (less than 5 years), the NPV Scheduler deterministic approach remains fit for purpose and computationally simpler.

References

Ataei, M., & Osanloo, M. (2003). Determination of optimum cutoff grades of multiple metal deposits by using the Golden Section search method. *Journal of the Southern African Institute of Mining and Metallurgy*, *103*(8), 493-499.

Ataei, M., Shahsavany, H., &Mikaeil, R. (2013). Monte Carlo Analytic Hierarchy Process (MAHP) approach to selection of optimum mining method. *International Journal of Mining Science and Technology*, *23*(4), 573-578.

Bhappu, R. R., & Guzman, J. (1995). Mineral investment decision making: A study of mining company practices. *Engineering and Mining Journal*, *70*(1), 36-38.

Collan, M. (2011). VALUATION OF INDUSTRIAL GIGA-INVESTMENTS: THEORY AND PRACTICE. *Fuzzy Economic Review*, *16*(1).

Dehghani, H., & Ataee-Pour, M. (2012). Determination of the effect of operating cost uncertainty on mining project evaluation. *Resources Policy*, *37*(1), 109-117.

Dehghani, H., Sakinezhad, R., Nabavi, Z., & Babanouri, N. (2024). Incorporation price uncertainty into open-pit to underground mine transition: Dehghani et al. *Mineral Economics*, *37*(1), 89-99.

Fan, X., Chen, K., & Chen, Y.-J. (2023). Is price commitment a better solution to control carbon emissions and promote technology investment? *Management Science*, *69*(1), 325-341.

Hajarian, A., Dambov, R., & Karanakova Stefanovska, R. (2011). Long Term Production Scheduling of Sungun Copper Mine Using NPV Scheduler Software.

Jiang, Y., & Dimitrakopoulos, R. (2024). Simultaneous stochastic optimisation of mining complexes with equipment uncertainty: Application at an open-pit copper mining complex. *Mining Technology*, *133*(3), 241-256.

Jiu, S., Guo, Q., & Liang, C. (2023). Robust optimization for integrating preventative maintenance with coal production under demand uncertainty. *IISE Transactions*, *55*(3), 242- .258

Kahraman, E., & Akay, O. (2022). Comparison of exponential smoothing methods in forecasting global prices of main metals. *Mineral Economics*, 1-9.

Lagos, T., Armstrong, M., Homem-de-Mello, T., Lagos, G., & Sauré, D. (2022). A framework for adaptive open-pit mining planning under geological uncertainty: T. Lagos et al. *Optimization and Engineering*, *23*(1), 111-146.

Li, X., & Maréchal, F. (2023). Deep excavation of the impact from endogenous and exogenous uncertainties on long-term energy planning. *Energy and AI*, *11*, 100219.

Madziwa, L., Pillalamarry, M., & Chatterjee, S. (2026). Mine Planning with Variable Price Input: A Case of Using Mine Planning Software. *Mining, Metallurgy & Exploration*, *43*(1), 253-262.

Mirzehi, M., & Afrapoli, A. M. (2024a). A novel framework for integrating environmental costs and carbon pricing in open-pit mine plans: Towards sustainable and green mining. *Journal of Cleaner Production*, *468*, 143059.

Mirzehi, M., & Afrapoli, A. M. (2024b). Sustainable long-term production planning of open pit mines: an integrated framework for concurrent economical and environmental optimization. *Resources Policy*, *94*, 105131.

Mirzehi, M., Rezakhah, M., Mousavi, A., & Nabavi, Z. (2023). New MIP model for short-term planning in open-pit mines considering loading machine performance: a case study in Iran. *International Journal of Mining and Mineral Engineering*, *14*(4), 341-364.

Nabavi, Z., Mousavi, A., Mirzehi Kalate Kazemi, M., & Monjezi, M. (2024). Incorporating grade uncertainty into open-pit long-term production planning using loss and profit functions. *International Journal of Mining and Geo-Engineering*, *58*(1), 59-67.

Parizanganeh, A., Hajisoltani, P., & Zamani, A. (2010). Assessment of heavy metal pollution in surficial soils surrounding Zinc Industrial Complex in Zanjan-Iran. *Procedia Environmental Sciences*, *2*, 162-166.

Quigley, M., & Dimitrakopoulos, R. (2020). Incorporating geological and equipment performance uncertainty while optimising short-term mine production schedules. *International Journal of Mining, Reclamation and Environment*, *34*(5), 362-383.

Rimélé, A., Dimitrakopoulos, R., & Gamache, M. (2020). A dynamic stochastic programming approach for open-pit mine planning with geological and commodity price uncertainty. *Resources Policy*, *65*, 101570.

Salehi, A., Afraei, S., & Shahriar, K. (2025). Optimizing the transition from open-pit to underground mining by simultaneously considering price and cost uncertainties. *Mining Technology*, *134*(4), 247-262.

Saliba, Z., & Dimitrakopoulos, R. (2019). Simultaneous stochastic optimization of an open pit gold mining complex with supply and market uncertainty. *Mining Technology*, *128*(4), 216-229.

Samala, T., Manupati, V. K., Machado, J., Khandelwal, S., & Antosz, K. (2022). A systematic simulation-based multi-criteria decision-making approach for the evaluation of semi–fully flexible machine system process parameters. *Electronics*, *11*(2), 233.

Savolainen, J., Rakhsha, R., & Durham, R. (2022). Simulation-based decision-making system for optimal mine production plan selection. *Mineral Economics*, *35*(2), 267-281.

Smith, L. (2002). Discounted cash flow analysis: Methodology and discount rates: Light metals. *CIM bulletin*, *95*(1062), 101-108.

Sohrabi, P., Dehghani, H., & Jodeiri Shokri, B. (2021). Determination of optimal production rate under price uncertainty—Sari Gunay gold mine, Iran. *Mineral Economics*, 1-15.

Sorabi, P., Ataei, M., Jazi, M. R. A., Dehghani, H., Shakeri, J., & Habibi, M. H. (2023). Application of Artificial Intelligence Techniques for Predicting the Back-break in Blasting Operation.

Tolouei, K., & Moosavi, E. (2023). Optimization of the production scheduling problem in open-pit mines to maximize the net present value using the human mental search algorithm. *Arabian Journal of Geosciences*, *16*(1), 16.

Tsoulos, I. G., & Charilogis, V. (2023). Locating the Parameters of RBF Networks Using a Hybrid Particle Swarm Optimization Method. *Algorithms*, *16*(2), 71.

Upadhyay, S. P., & Askari-Nasab, H. (2018). Simulation and optimization approach for uncertainty-based short-term planning in open pit mines. *International Journal of Mining Science and Technology*, *28*(2), 153-166.

Xu, X., & Zhang, Y. (2022). Coking coal futures price index forecasting with the neural network. *Mineral Economics*, 1-11.