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Exploitation of Mineral Resources in Conditions of Volatile Energy Prices: Technical and Economic Analysis of Low-Quality Deposits

Zbigniew Krysa [1,*], Przemysław Bodziony [2] and Michał Patyk [2]

[1] Department of Mining, Faculty of Geoengineering, Mining and Geology, Wroclaw University of Science and Technology, 50-370 Wroclaw, Poland
[2] Department of Mining Engineering and Work Safety, Faculty of Civil Engineering and Resource Management, AGH University of Kraków, 30-059 Krakow, Poland; przembo@agh.edu.pl (P.B.); mpatyk@agh.edu.pl (M.P.)
* Correspondence: zbigniew.krysa@pwr.edu.pl

Abstract: In mining projects and production operations, energy carrier costs (fuel, electricity) constitute the primary component of variable costs. This study outlines a methodology for projecting operating costs in a surface mine or quarry in order to find the optimal configuration of mining equipment to extract low-grade secondary deposits, taking into account volatile energy prices. For illustration, the operating costs of five variants of mining equipment deployed to mine low-grade products were analysed, with the price of energy and fuels being the key cost component and the main risk factor. There were differences between the initial investment outlays and operating costs involved in all analysed variants, whilst the starting point for estimating the technical and economic parameters involved in the respective solutions was the predefined configuration of the mining equipment. Further, the decision to commence or discontinue mining operations could be supported by the simulation procedure based on the economic model. The results provided valuable insights into the cost-effectiveness of low-grade deposit extraction scenarios, depending on the projected unit costs of fuels and energy.

Keywords: energy carrier prices; heavy mining equipment; secondary deposit; cost analysis

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1. Introduction

Due to complex geological and mining conditions in quarries and mines, low-grade secondary deposits are often found close to currently mined areas. The presence of intrusions and interlayers makes it difficult to mine the target deposit. In limestone quarries, secondary mineralised zones are often interspersed with karst features. It is common practice to dump these sections as waste rock or to leave them undisturbed, which has a negative impact on profitability, technology and the environment [1]. Mining practice has shown that even when secondary mining is planned, it is often never started, and the entire section is hauled to the dump [2,3].

Another concern is the need to promote sustainable mining practices in mines and quarries to ensure optimal use of deposits, which requires selective extraction [1,4,5]. This approach helps to limit the area of the mine site and reduce the size of the tailings pile by producing smaller quantities of waste rock [4]. To date, the exploitation of secondary deposits, previously treated as waste rock, is more common in rare earth mining [6–8]. In mining and quarrying, secondary deposits become a significant problem when overlying strata are removed to access the target deposit. Treating waste rock as a low-grade portion of the deposit is a critical factor in mining economics, as only the portion that cannot be reused needs to be dumped, thereby reducing the total waste [9,10].

The viability of mining secondary deposits should be subject to thorough analysis due to the lower value of the minerals produced. Furthermore, due to the high volatility of

fuel and energy costs, particularly in relation to other costs, subsequent estimates based on adopted assumptions may indicate the profitability or unprofitability of the mining operation, and once the investment decision is finally made (particularly when it involves the purchase of machinery and equipment), it is the mining company that has to deal with the consequences [9,10].

The use of waste rock deposits and waste after limestone processing was investigated in [11–14], though the studies were not supported by economic analyses. Extensive analyses of operating costs in the mining sector are provided in [15–24]. The actual proportions of operating costs and capital expenditures involved in haulage operations in an open-pit mine were given by Demir, E. et al. [25] and Hajarian, A. and Osanloo, M. [26]. Also, Rodovalho, E. [27] and Ercelebi, S. and Bascetin, A. [28], as well Choudhary, R. [29] and Ozdemir, B. and Kumral, M. [30] propose a cost model that considers all activities in the mining cycle and takes a system-wide approach to minimizing the total cost of bench production. Guo, H. et al. [31] used artificial intelligence to estimate costs in open-pit copper mining, and this issue was also addressed in [32]. Valle de Souza, S. et al. [33] conducted an empirical analysis of mining costs in Australia. Dougall, A. and Mmola, T. [34] identified key performance areas in southern African surface mining. Budeba, M. et al. [35] proposed a model for estimating the cost and technical efficiency of a surface mine. Teplická, K. et al. [36] summarized the research work focused on the use of economic indicators to value the efficiency and functionality of mining processes. Da Gama, C. [37] presented the methodology used in each phase of an open-pit mining project to assess its current technical and economic feasibility. Costa Lima, G. and Suslick, S. [38] explored the price and cost volatility in the mining industry.

The underlying model is the nonlinear time series model with the Gaussian copula as the generator of random variables (prices) with predefined distributions. This tool is applied to design the portfolio of financial instruments to minimize the investment risk, as described by Ghorbel, A. and Trabelsi, A. [39] and Fenech, J.P. and Vosgha, H. [40]. Applications of the copula-based approach combined with the systematic risk analyses are explored by Hochrainer et al. [41] and Fernandes, M.C. et al. [42]. With regard to the mining industry and geology, Krysa et al. [43] used the copula-based approach to estimate the profitability of mining projects, making use of the nonlinear nature of the dependence between the price of copper and silver to represent the variability in the project's value.

In the literature review conducted, no article was found that simultaneously analysed the structure of production costs in the mining industry and estimated the impact of cost components in a mid-term perspective. In the analyses of the authors cited so far, these aspects have been treated separately or not at all, so this article attempts a multi-faceted techno-economic analysis of the issue of the impact of the variable cost components of energy carriers on the profitability of production in the area of mineral resource exploitation, where energy consumption in the transportation process is a key factor determining profitability.

2. Materials and Methods

The case study analysis was conducted to support the selection of mining equipment to be deployed in a surface limestone quarry where intermediate karts features are found so that 30% of the deposit is regarded as waste rock and thus should be hauled to a dumping site. The predetermined output level was taken to be 600 Mg/h for each configuration of the mining equipment operation. Apart from haul trucks, all machines are effectively used during the two active work shifts for T_e = 7 h (T_e—shift effective time). It was assumed that the machines would be used for 25 days in a month, totalling 350 h.

Respective configurations of mining equipment that can be deployed to mine secondary limestone deposits are summarised below (Figure 1). These include the selected equipment and machinery, as well as the settings, such as haulage roads systems. The mining company selected the sets of mining equipment from the pool of available machines, with an objective to rely more on electrically powered machines to limit the fuel

oil consumption (and its costs) and to reduce the greenhouse gas (GHG) emissions. Five machine systems were thus configured, and all technical parameters and the waste rock content in the currently excavated deposit section were duly taken into consideration. Variable parameters in respective variants include the number and type of machines and equipment, the number of machine operators and the length of haulage roads. Another issue associated with the performance of the configured machine system is the feasibility of operating a mobile crusher (MCON) positioned in the proximity of the highwall, which might interfere with blasting works in variant W1. In addition, the crusher in variant W1 was positioned in the vicinity of the central haulage road, disturbing the transport activities. It was therefore suggested that the location of the primary crushing should be moved so that the crushing system could incorporate an electrically powered crusher (MCE)—variant W2—or a stationary crusher (SC2)—variant W3. Further, the use of a stationary crusher allows the output to be increased through double crushing. Depending on the specificity of the respective variants, the haul trucks should be used for the following:

- Hauling the mined material to the initial crusher (SC2 or MCON);
- Hauling the mined material to the aggregate mining plant (AMP);
- Hauling the mined material to the external dumping site (ED).

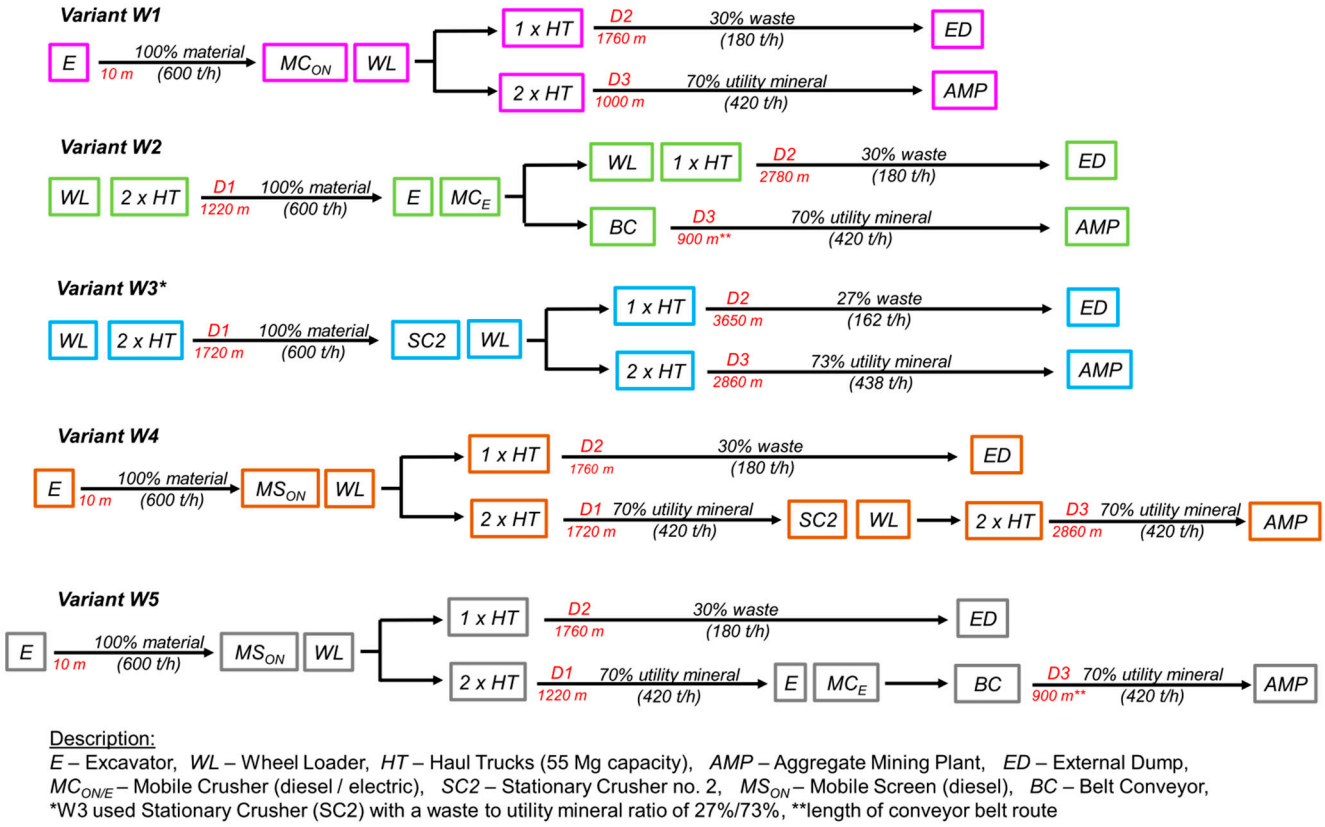


Figure 1. Configuration of the mining equipment based on various decisions.

In variant W2, a belt conveyor is used to transfer the intermediate product from the excavation site to the aggregate mining plant (AMP). Variants W4 and W5 are modified versions of W3 and W2, whereby a mobile screen is provided near the highwall to shorten the haulage road where the low-grade material is carried and to eliminate the double haulage of the mined material to the primary crusher. The costs of blasting works, which remained unchanged in each considered variant, were omitted for further analysis, as they have no bearing on the overall operating costs in all variants. We use the following labels: D1—mined material transported to the crusher; D2—waste rock transported to the

dumping site; and D3—transport of the half-finished product from the aggregate mining plant.

This study uses a tool to estimate the probability that a given mining production scenario in a rock mine or quarry will be profitable based on actual mine site data, whilst the individual risk (due to the variability of fuel and energy prices) is integrated with technical and economic aspects of the mining company operation (Table 1). The starting point in the analysis was the 4-year period of 2019–2022, when fuel and energy costs were fluctuating a great deal. Actually, the year 2019 marked the end of a stability period which had lasted for several years. In 2020, the prices of fuels and energy carriers dropped significantly, followed by a reduced demand for rock materials. In 2021, both the prices and demand for rock materials increased slightly and then stabilised, while in 2022, there was sharp increase in the prices of all energy carriers.

Table 1. Example of operating costs of mining equipment based on the 1st year of input data.

Machine	Leasing	TMNR *	Payroll	Fuel	Energy	Tires
E—Excavator	27,300	5250	4500	105,241	-	-
WL—Wheel Loader	50,000	17,472	5175	107,940	-	3500
MCON—Mobile Crasher diesel	48,500	12,000	-	75,558	-	-
MCE—Mobile Crasher electric	48,500	5000	-	-	40,404	-
SC2—Stationary Crasher no. 2	0	107,297	9000	-	284,739	-
MSON—Mobile screen (diesel)	20,000	5000	-	59,367	-	-
BC—Belt conveyor	2380	3000	-	-	39,312	-
HT—Haul trucks	42,000	17,000	4500	*	-	5600

* TMNR—total maintenance and repair.

The overview of energy prices as the input to the estimation/prediction model includes the total operating costs of the mining equipment in each configuration until the end of 2022. Cost projections covering the years of 2023–2026 and taking into consideration fluctuating prices of energy carriers are based on distribution functions in multivariate probability distributions.

The case study analysis of the feasibility of secondary deposit exploitation involves three steps.

Step I summarises the respective configurations of the mining equipment with itemised operating costs over the years of 2019–2022 and thoroughly analyses the estimated variable operating costs in each system configuration, highlighting the main cost components (fuel oil and electricity prices).

2.1. Step I—The Operating Costs of the Mining Equipment

The operating costs of the mining equipment in respective configurations were analysed and collated in a detailed comparative study of the key cost components in variants W1–W5 over the years of 2019–2022. The key components of the operating costs in each configuration were categorised and subjected to an empirical analysis in the context of secondary deposit mining. These costs include the following:

- Costs of fuel or/and electricity;
- Leasing costs;
- Total maintenance and repair costs;
- Costs of tyres in haul trucks;
- Personnel costs—payroll.

The costs of fuel consumption were calculated considering the operating time of machines over one month (350 h), the average prices of one litre of diesel oil and electricity (1 kWh), the average fuel and power consumption for machines and the average planned

fuel consumption over a given transport route for haul trucks, as well as the number of active shifts.

$$\begin{cases} C_{E_{Vi}} = C_{E.H_{Vi}} + C_{E.M_{Vi}} \\ C_{E.H_{Vi}} = C_{E_{Vi.D1}} + C_{E_{Vi.D2}} + C_{E_{Vi.D3}} \\ C_{E.M_{Vi}} = D \cdot T_e \cdot Z \cdot \left[\sum Q_{DF_k} \cdot P_{DF} + \sum Q_{EL_k} \cdot P_{EL} \right] \end{cases} \quad (1)$$

where the following apply:

$C_{E_{Vi}}$—total costs of energy carriers for the mining equipment in the *i*-th variant, EUR/month;
$C_{E.H_{Vi}}$—fuel consumption costs for the transport equipment in the *i*-th variant, EUR/month;

And

$$C_{E_{Vi.Dj}} = Q_{DF.Dj} \cdot D \cdot T_e \cdot Z \cdot P_{DF} \quad (2)$$

$C_{E_{Vi.Dj}}$—fuel consumption costs for the haul truck in the *i*-th variant along the *j*-th route, EUR/month;
$Q_{DF.Dj}$—average fuel consumption of the transport equipment operating along the *j*-th route, L/h;
D—number of working days;
T_e—effective shift time;
Z—number of shifts, pcs;
P_{DF}—average net price of diesel fuel, EUR/L;
$C_{E.M_{Vi}}$—costs of energy carriers for one unit within the machine systems in the *i*-th variant, EUR/month;
Q_{DF_k}—average fuel consumption by the *k*-th machine, L/h;
Q_{EL_k}—average power uptake by the *k*-th machine, kWh;
P_{EL}—average net price of electricity, EUR/kWh.

Labour costs depend on the number of employees and their actual wages (3). The average gross wage was contingent upon the classification of employee categories.

$$\begin{cases} C_{W_{Vi}} = C_{W.H_{Vi}} + C_{W.M_{Vi}} \\ C_{W.H_{Vi}} = C_{W.H_{Vi.D1}} + C_{W.H_{Vi.D2}} + C_{W.H_{Vi.D3}} \\ C_{W.M_{Vi}} = n_{op_{Vi}} \cdot C_W \end{cases} \quad (3)$$

where the following apply:

$C_{W_{Vi}}$—total labour costs (payroll), EUR/month;
$C_{W.H_{Vi}}$—costs of haul truck drivers in the *i*-th variant, EUR/month;
$C_{W_{Vi.Dj}}$—haul truck driver wages in the *i*-th variant on the *j*-th route:

$$C_{W_{Vi.Dj}} = n_{H_{Vi.Dj}} \cdot Z \cdot C_W \quad (4)$$

$n_{H_{Vi.Dj}}$—number of haul trucks in the *i*-th variant, pcs;
C_W—machine operator wages, EUR/month;
$C_{W.M_{Vi}}$—wages of loader, crusher-screen and belt conveyor operators in the *i*-th variant, EUR/month;
$n_{op_{Vi}}$—number of machine operators in the *i*-th variant, pcs.

Leasing costs in individual variants depend on the actual configuration of the deployed equipment, which has been calculated using the following formulas:

$$\begin{cases} C_{L_{Vi}} = C_{L.H_{Vi}} + C_{L.M_{Vi}} \\ C_{L.H_{Vi}} = C_{L.H_{Vi.D1}} + C_{L.H_{Vi.D2}} + C_{L.H_{Vi.D3}} \\ C_{L.M_{Vi}} = \sum C_{L_k} \end{cases} \quad (5)$$

where the following apply:
$C_{L_{Vi}}$—total leasing costs in the *i*-th variant, EUR/month;
$C_{L.H_{Vi}}$—haul trucks leasing costs in the *i*-th variant, EUR/month;

$C_{L.H_{Vi.Di}}$—haul truck leasing costs in the *i*-th variant on the *j*-th route:

$$C_{L.H_{Vi.Dj}} = n_{H_{Vi.Dj}} \cdot Z \cdot T_e \cdot D \cdot C_{L_H} \quad (6)$$

$n_{H_{Vi.Dj}}$—number of haul trucks in the *i*-th variant, pcs;
C_{L_H}—leasing costs for haul trucks, EUR/hour;
$C_{L.M_{Vi}}$—costs of leasing of loaders, crusher-screens and belt conveyors in the *i*-th variant, EUR/month;
C_{L_k}—leasing costs for the *k*-th machine operating in a given configuration, EUR/mining equipment.

The total maintenance and repair costs of haul trucks depend on the number of machines and the usage rate of the dump bed. For other machines, the TMNR cost depends on their number and unit cost.

$$\begin{cases} C_{TM_{Vi}} = C_{TM.H_{Vi}} + C_{TM.M_{Vi}} \\ C_{TM.H_{Vi}} = C_{TM.H_{Vi.D1}} + C_{TM_{Vi.D2}} + C_{TM_{Vi.D3}} \\ C_{TM.M_{Vi}} = \sum C_{TM_k} \end{cases} \quad (7)$$

The procedure to calculate these costs was similar to that adopted in the previous section, where the following apply:

$C_{TM_{Vi}}$—TMNR costs in the *i*-th variant, EUR/month;
$C_{TM.H_{Vi}}$—TMNR costs for haul trucks in the *i*-th variant, EUR/month;
$C_{TM.H_{Vi.Dj}}$—haul truck TMNR costs in the *i*-th variant on the *j*-th process route:

$$C_{TM.H_{Vi.Dj}} = n_{H_{Vi.Dj}} \cdot Z \cdot T_e \cdot D \cdot C_{TM_H} \quad (8)$$

$n_{H_{Vi.Dj}}$—number of haul trucks in the *i*-th variant, pcs;
C_{TM_H}—TMNR costs for haul trucks, EUR/hour;
$C_{TM.M_{Vi}}$—TMNR costs of loaders, crusher-screens and belt conveyors in the *i*-th variant, EUR/month;
C_{TM_k}—TMNR amount for the *k*-th machine operating in a given configuration, EUR/mining equipment.

2.2. Step II—The Forecasts of the Operating Costs of Mining Equipment

In Step II, forecasts were made of the operating costs of mining equipment for the next 4 years using a simulation model based on a univariate model and the copula-based approach and integrating the distribution functions of a two-dimensional probability distribution. The aim of the simulation procedure was to find the most probable scenario of cost values for the respective variants of mining operations. Future cash flow estimates were obtained based on time series simulations of electricity and fuel oil prices, i.e., two major components of operating costs, which are strongly affected by the broadly understood market risk.

The level of complexity of economic models that are used to evaluate the efficacy of a given solution is largely dependent on the accuracy of the input data. In the case of simple models wherein the input data are aggregates of a variety of accounting entries (production costs, gross revenue, investment outlays), the traditional approach comparing cash flows in subsequent time periods is found to suffice. However, when the relative influence of a given parameter (for example, electricity or fuel price) needs to be assessed, a more detailed model is required. With models involving simulation of defining probability distribution parameters, it is required that the historical time series data should be applied.

The simulation procedure was conducted using two variants of the prognostic model. In the first variant, the generated time series are assumed to be series-independent, and no cause-and-effect relationship between the electricity and fuel oil price is observed in

the short-term. In the second model, underlying the profitability analysis is the simulation model capturing the relationships between the electricity and fuel prices.

Modelling taking fluctuating prices of energy carriers into account enabled the identification of the riskiest and most cost-effective configurations. The cost-effectiveness of each considered variant is taken into account, and the price of the end product is assumed to be the minimal price allowing for the balancing of the total costs, including the variable dumping costs.

Historical data were treated statistically, focusing on the prices of electricity and fuel oil. The data covering the years of 2019–2022 were found adequate to capture the existing market conditions, which have a bearing on price levels and price fluctuations. The proposed time period is sufficiently long to capture both short- and long-term patterns of supply and demand in the fuel and energy markets. In light of the classical approach to business cycles, the analysed period covers 2–3 short-time cycles when the price fluctuations are the result of stock levels and users' responses to existing market conditions. Further, such a time period extends over at least one mid-term cycle, in which price fluctuations are attributable to the levels of investments in fixed assets and structural adaptations in the market economy, which are major determinants of the supply and demand for raw materials. Were a longer time period considered, the model would have to handle price fluctuations due to reasons which can hardly be categorised as adequate in the light of the current market conditions. The decision of which model of time series simulation to choose was based on the information criteria, i.e., indicators which show how well a model fits the data that it was generated from. In the present study, the Akaike information criteria, as well as the Schwartz and Hannan–Quinn criteria, were applied, which were also utilised for modelling energy carrier prices [44].

In price modelling, the one-dimensional time series models is applied, and price fluctuations are attributed solely to the back history of the variable and are the function of the rate of return r_t:

- Fuel oil price—MA model (moving average):

$$r_t = \mu + A1((r_{t-1}) - \mu) + A2((r_{t-1}) - \mu) + \sigma \cdot z_t \quad (9)$$

where the following apply:

r_t—log return due to price variation;
μ—mean value (log returns);
$A1$, $A2$—autoregression coefficients of the order 1 and 2;
σ—standard deviation of log returns;
z_t—white noise (standardised error).

- Electricity price (APARCH Asymmetric Power Autoregressive Conditional Heteroskedosticity model) [45]:

$$r_t = \mu + \sigma \cdot z_t \quad (10)$$

where

$$\ln(\sigma_t^2) = \omega + a|(r_{t-1}) - \mu| + \gamma((r_{t-1}) - \mu)^{\delta} + b\sigma_{t-1}^2 \quad (11)$$

$$g(z_t) = \theta z(t) + |z_t| - 0.797885 \quad (12)$$

θ, ω, a, b—regression model parameters;
σ_t^2—conditional variance.

The value 0.797885 is $\sqrt{2/\pi}$, which is the expected value of the absolute value of a standard normal random variable N(0, 1).

2.3. Step III—Analysing the Profitability of Mining Operations Using the Created Economic Model

Steps I and II yielded the financial model for the purpose of simulations, and the main relevant economic parameters to the operation of mining processes were defined for the considered variants. The total costs involved in mining operations in all variants were determined, and the break-even point was established for the next years of continuing mining operations.

In Step III, the outputs from Step I and Step II were integrated into one model. The procedures for calculating the profitability of a mining production were combined with the model for simulating the volatility of electricity and fuel prices, thus obtaining an analytical–prognostic model. The model was applied to estimate key economic parameters, affording us the means to estimate the profitability of deposit extraction.

The principle behind the model is relatively simple. The values of the time series of electricity and fuel prices generated in subsequent iterations were transferred to economic models of respective variants, providing information about the unit costs. The unit costs were then recounted in terms of global costs, in accordance with formulas derived in Step I, and registered in the cost structure for individual variants to enable their relative rating.

3. Results and Discussion

In Step I, all cost components of a mining equipment operation were identified, and the cost structures of variants W1–W5 were determined accordingly, alongside the analysis and comparison of costs involved in secondary deposit mining over the years of 2019–2022 (Tables 2–5 and Figure 2).

Table 2. Summary of cost components in all variants of mining equipment operations in 2019.

2019	Leasing	TMNR	Payroll	Fuel ON	Energy	Tiers
W1	762,797	212,242	117,947	194,408	-	51,097
W2	923,083	246,595	134,590	208,980	29,383	51,097
W3	935,748	568,882	206,950	220,578	104,953	79,211
W4	1,080,486	595,020	221,422	275,505	104,953	79,211
W5	914,821	228,179	132,419	224,643	29,383	51,097

Table 3. Summary of cost components in all variants of mining equipment operations in 2020.

2020	Leasing	TMNR	Payroll	Fuel ON	Energy	Tiers
W1	792,546	220,519	124,198	158,443	-	51,628
W2	959,083	256,212	141,723	170,318	24,273	51,628
W3	972,242	591,069	217,918	179,770	86,700	80,034
W4	1,122,625	618,226	233,157	224,538	86,700	80,034
W5	950,499	237,078	139,437	183,083	24,273	51,628

Table 4. Summary of cost components in all variants of mining equipment operations in 2021.

2021	Leasing	TMNR	Payroll	Fuel ON	Energy	Tiers
W1	825,040	229,560	135,252	208,015	-	52,165
W2	998,405	266,717	154,336	223,608	35,770	52,165
W3	1,012,104	615,303	237,313	236,018	127,768	80,867
W4	1,168,653	643,573	253,908	294,790	127,768	80,867
W5	989,469	246,798	151,847	240,368	35,770	52,165

Table 5. Summary of cost components in all variants of mining equipment operations in 2022.

2022	Leasing	TMNR	Payroll	Fuel ON	Energy	Tiers
W1	900,119	250,450	151,617	374,720	-	52,734
W2	1,089,260	290,988	173,011	402,810	49,823	52,734
W3	1,104,206	671,295	266,027	425,163	177,963	81,749
W4	1,275,000	702,138	284,631	531,035	177,963	81,749
W5	1,079,511	269,257	170,220	432,998	49,823	52,734

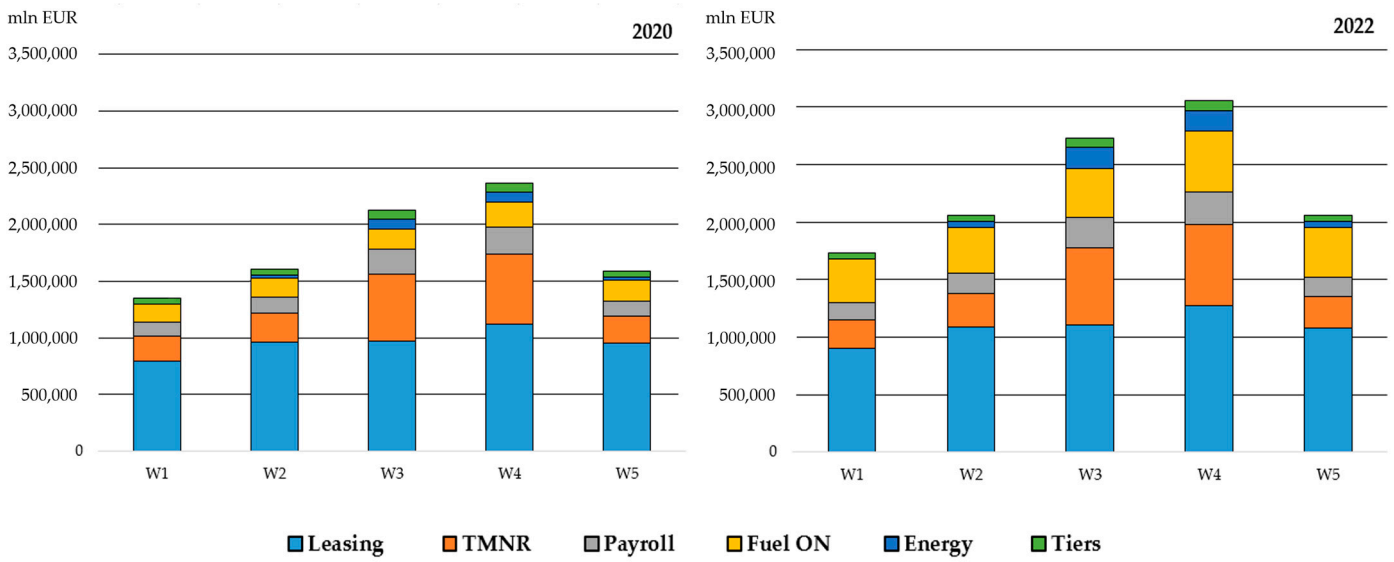


Figure 2. Cost structure in all configurations of mining equipment for 2020 and 2022.

The analysis revealed that the cost of energy carriers and fuels would be the main cost component in all the considered variants. In variant W1, this cost accounted for 45% of the total costs, and in 2022, this proportion rose to 55%, which is a 10% increase relative to earlier years. In variants W2 and W5, the sum of energy carriers and fuel costs amounted to 48% of the total operating costs, rising to 58% in 2022. It is worth mentioning that mining operations in these two variants use both diesel-powered and electrically powered machines, whilst the electricity price accounts for 5–6% of the total costs. The relative share of the electricity price is the largest in variant W3 and W4, accounting for 15% of the total costs, whilst the relative share of fuel oil costs is 35%. The totalled average share of these costs is 48% of the total operating costs, rising to 58% in 2022. It appears that in 2022, the costs of fuels and electricity rose by 10% in relation to previous years, accounting for more than half of the total operating costs.

Below is a summary of the estimated operating costs in each variant, taking into account price volatility and assuming planned production levels and variable costs of dumping in line with the prices of energy carriers over the years of 2019–2022 (Tables 6 and 7).

Table 6. Total costs in all variants of mining equipment operation over the years of 2019–2022.

	2019	2020	2021	2022
W1	1,338,490	1,347,333	1,450,032	1,729,641
W2	1,593,727	1,603,236	1,731,001	2,058,626
W3	2,116,321	2,127,733	2,309,371	2,726,402
W4	2,356,596	2,365,279	2,569,558	3,052,515
W5	1,580,540	1,585,996	1,716,417	2,054,542

Table 7. Dumping costs in all variants of mining equipment operation over the years of 2019–2022.

	2019	2020	2021	2022
W1	945,000	913,500	1,039,500	1,260,000
W2	945,000	913,500	1,039,500	1,260,000
W3	850,500	822,150	935,550	1,134,000
W4	945,000	913,500	1,039,500	1,260,000
W5	945,000	913,500	1,039,500	1,260,000

The analysis revealed how the costs, cost structure and revenues of mining companies changed over the years. In the investigated period, all costs involved in mining operations (total operating costs + dumping costs) fell by 6% in 2019 in relation to 2020, and then rose by 15% in 2021 and by 34% in 2022 (relative to the cost levels in 2021). There was a 45.2% increase in costs within the considered period of time (2022/2019). In response to the cost increase, the analysed quarry and the entire extractive industry increased the price of their products. In the case of the analysed quarry, there was a 10% increase in 2020 in relation to the price levels in 2019; in 2021, the prices rose by 18%; and in 2022, they rose by 15% in relation to 2021. In the investigated period of time, the total price increase was 50%. The analysis revealed that variant W1 using exclusively diesel-powered machines is most resilient to cost volatility (fluctuating prices of energy carriers), even though the price of fuel oil rose by 80%, while the electricity price increased by nearly 40%.

Step II focused on projections of operating costs of mining equipment in the years of 2023–2026 using a simulation model based on a univariate model (Equations (9)–(12)) and an empirical copula-based approach connecting the probability distribution functions of the two-dimensional probability distributions. In the case of the variant whereby the price levels are generated with the copula function, the price simulations used the parameters and the estimated copula function based on empirical data. The scatter of input data and of 10,000 points generated accordingly are shown in Figure 3.

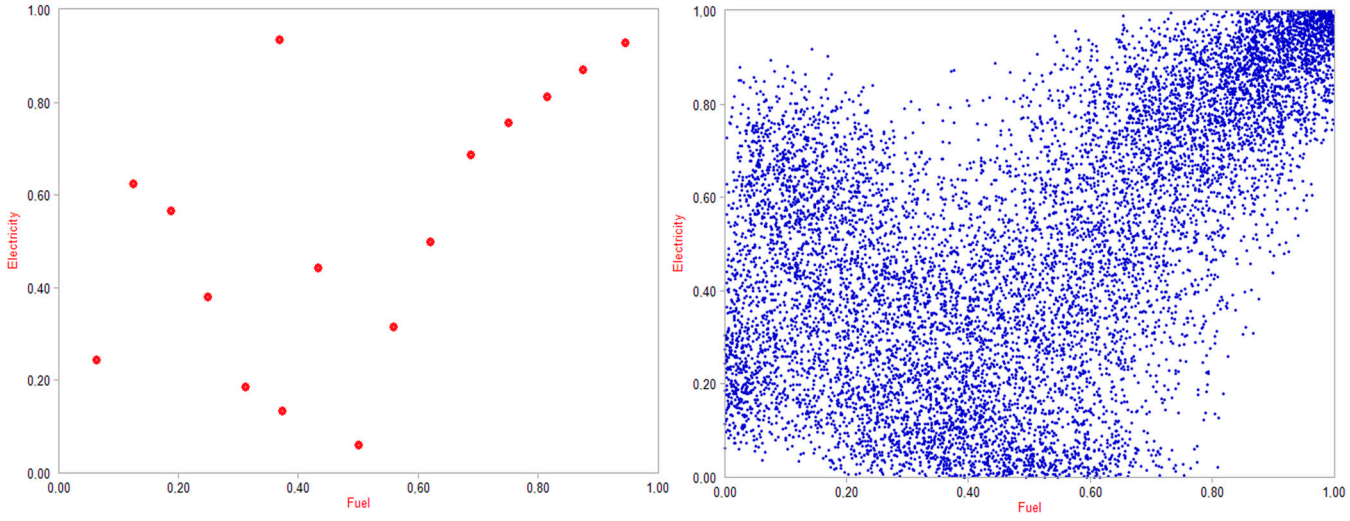


Figure 3. Input data (**left**) and simulated empirical copula (**right**) for electricity and fuel prices.

The axes represent the electricity price (variable 1) and fuel oil price (variable 2). The range of input data, including two times series with 15 elements each, seems rather narrow. This is because price volatility due to fluctuations on the local markets or short-term fluctuations of the electricity price was omitted in the economic analysis of mining profitability. The input data for assessing the correlation between fuel and electricity prices were the averaged quarterly prices recorded in the period of 2019–2022 (Table 8), and thus,

the historical coherence was retained between the mining cost data in particular variants and the market prices of fuels and electricity.

Table 8. Average prices of electricity and fuel oil from 2019 to 2022 [46,47].

Cost	2019	2020	2021	2022
Electricity [EUR/kWh]	0.115	0.095	0.14	0.195
Fuel ON [EUR/L]	1.00	0.815	1.07	1.928

For the purpose of projections, 10,000 simulations of the time series were conducted for assets involved in the copula-based model (Figure 4); the *X*-axis represents the electricity price, and the *Y*-axis represents the fuel oil price. Each set of input data (price vector) comprised 30 elements (historical averaged quarterly price data for the last 6 years), and the time series models were derived accordingly using the ModelRisk program v 6.1.98.

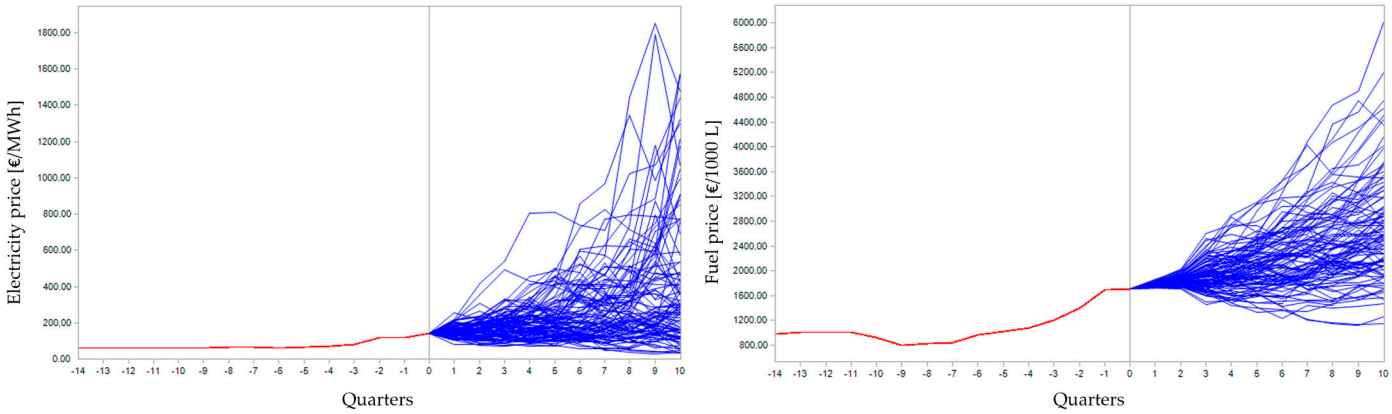


Figure 4. Historical (red series) and simulated prices in the model (blue series) of electricity, EUR/MWh, in APARCH model (**left**) and diesel, EUR/1000 L, (**right**) in MA2 model up to the year 2026 (quarterly unit).

The range of simulation results for the prices of energy carriers used as inputs to the economic model is depicted in the following Figure 5 and Table 9.

Table 9. Statistical treatment of simulation data: electricity and fuel oil prices.

Cost	2023			2024		
	Av.	**St. dev.**	**Range**	**Av.**	**St. dev.**	**Range**
Electricity price [EUR/kWh]	0.16	0.02	0.12–0.32	0.20	0.05	0.11–0.56
Fuel ON [EUR/L]	2.00	0.30	1.17–3.57	2.35	0.56	1.10–5.77
	2025			**2026**		
	Av.	**St. dev.**	**Range**	**Av.**	**St. dev.**	**Range**
Electricity price [EUR/kWh]	0.24	0.08	0.10–0.73	0.29	0.10	0.10–0.95
Fuel ON [EUR/L]	2.79	0.84	1.04–713	3.33	1.20	0.89–12.17

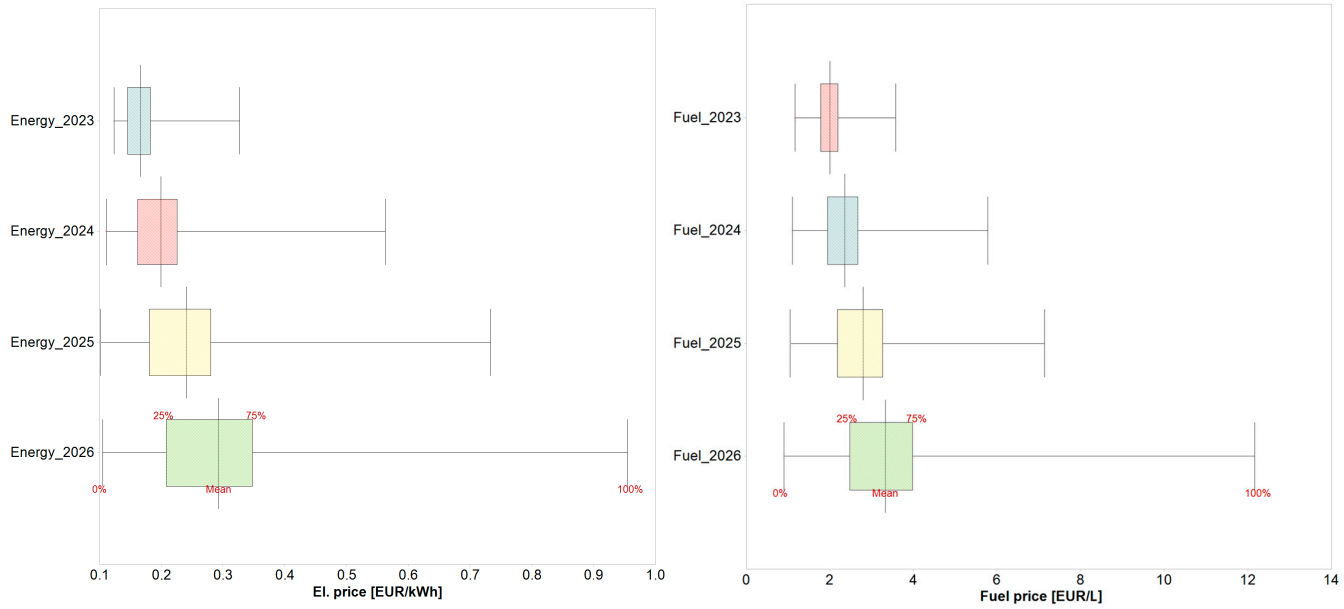


Figure 5. Simulation of electricity and fuel oil prices in the economic model of mining operation.

The simulation data are indicative of the increasing cost of electricity and diesel oil in the next years of projected mining operations. As regards electricity prices, the modelled cost is expected to increase from 0.16 to 0.29 EUR/kWh, marking an average 81% increase over the 4-year period. In the case of fuel oil price simulation, the modelled increase is less significant, and the price level is expected to rise from 2 to 3.33 EUR/L, making it a 66% increase on average. The profitability of the respective variants is affected not only by the average simulated price levels, but also by the actual range of price variability. Evidently, the results for subsequent years fall in broader intervals, expressed in terms of the price range and their standard deviation (comparison between simulation data).

As regards electricity price fluctuations, the simulated prices fall in the interval of 0.12–0.32 EUR/kWh, giving the statistical range of 0.2 for 2023. Each year, the price is expected to rise to 0.10–0.95, giving the static range of 0.85 (a 4-fold increase). Similar conclusions can be drawn when comparing results based on the standard deviation. For fuel oil prices, the range of simulation results for 2023 falls in the range 1.17–3.57, giving the spread of 2.4 EUR/L. For the last year in the considered period, the statistical range of simulation data falls in the interval of 0.89–12.17 EUR/L, giving the spread of 11.28.

With regard to the importance of the fuel oil as the major determinant of mining profitability, the conclusion can be drawn that the simulated broad statistical range of electricity and fuel prices should be the main consideration when deciding which variant of mining operations to choose.

In Step III, the performance of the economic model of the mine was assessed through simulations covering the subsequent years of mining operations. The key parameter in modelling was the break-even price of the marketed product. The respective variants reflected various levels of investment outlays and variable costs to be borne. Assuming that the selling price of the product is independent of the mining plant (market price), it is reasonable to assume that the break-even price is the right measure to adequately evaluate the variants. The average selling price at the break-even point was determined for the subsequent years of mine operation using the classic break-even price formula (Table 10), based on the projected levels of fixed and variable costs and production figures. The fundamental assumption of the break-even model is that production costs will increase, as indicated by the increasing break-even price for the later years of the simulation. The increase in price, measured on average for each variant, is approximately 50%.

Table 10. Average break-even price in subsequent years of mining operations for all variants [EUR/Mg].

Variant	2023	2024	2025	2026
W1	10.46	11.97	13.68	15.73
W2	11.80	13.48	15.39	17.70
W3	13.53	15.41	17.53	20.15
W4	16.05	18.31	20.85	23.98
W5	12.00	13.74	15.71	18.08

The distribution of results for the subsequent years of the break-even simulation is shown using variant W1, the most profitable in terms of break-even price (Figure 6), and variant W4, the least profitable, which generates the highest required break-even price (Figure 7).

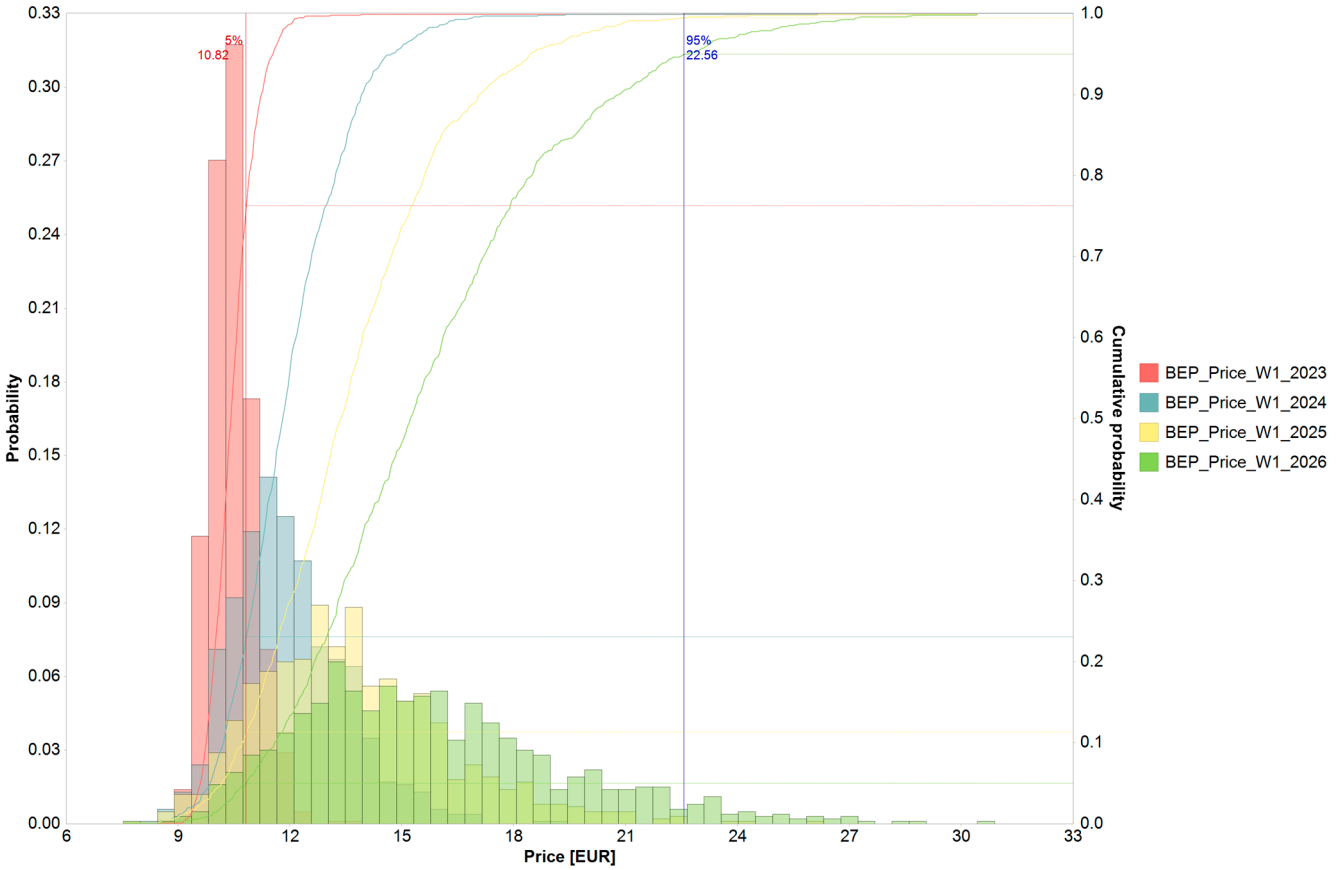


Figure 6. Break-even price: variant 1 (the most economically advantageous).

The simulation of the break-even price reveals the increasing price volatility in subsequent years. With regard to the figures for 2023 for variant W4 (Figure 7), the price falls in the interval from 13.28 EUR/Mg to 22.73 EUR/Mg (statistical range 9.45 EUR/Mg). The 90% confidence interval of the averaged break-even price falls in the range of 14.62–17.96 EUR/Mg. The results for subsequent years show the wider scattering and distribution of the break-even price data, which vary significantly. The range of simulation results (break-even price) for the final year (2026) is from 12.60 to 47.12 EUR/Mg, with the spread being 34.52 EUR/Mg, marking a 3.5-fold increase in relation to 2023. The 90% confidence interval falls in the range of 16.83–33.73 EUR/Mg, with the spread being 16.90 EUR/Mg, marking a 5-fold increase in relation to 2023.

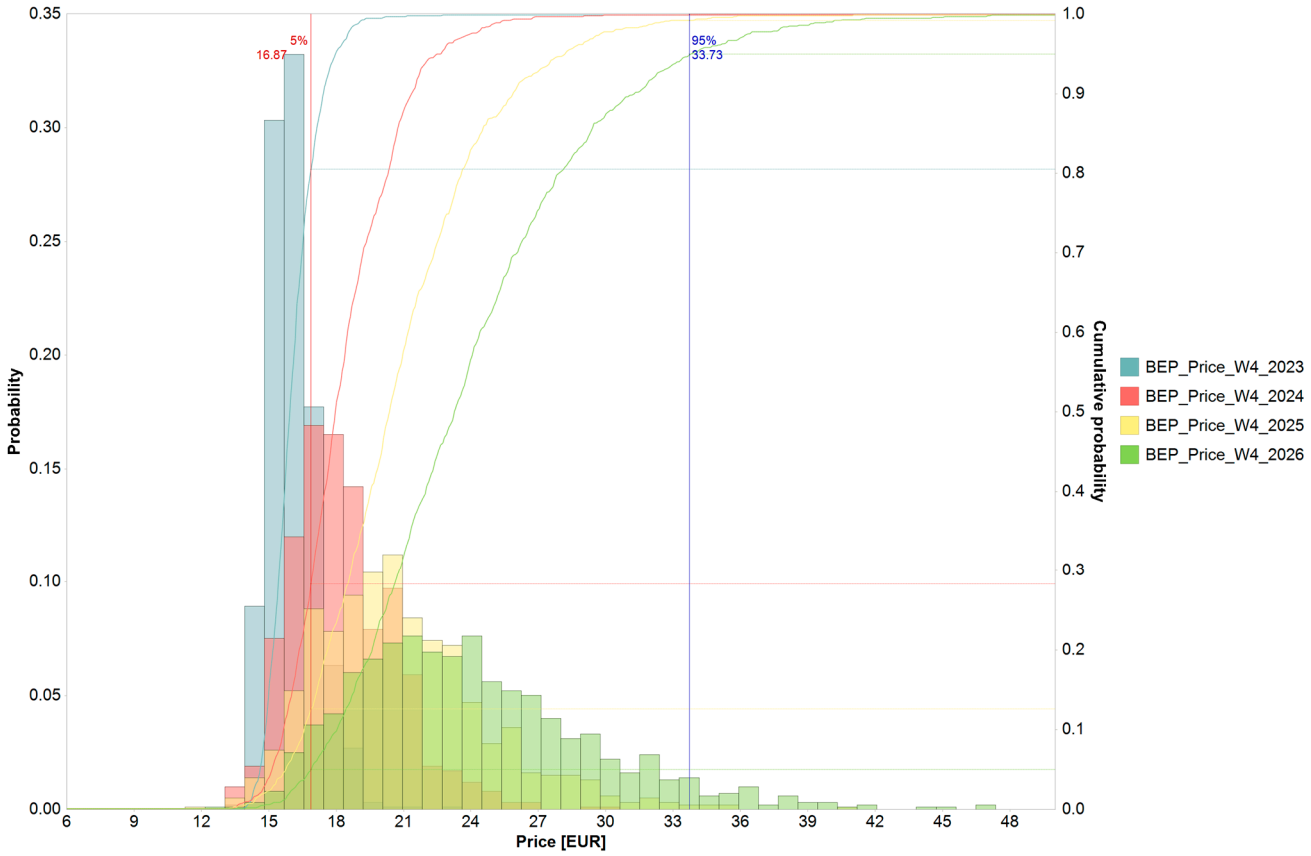


Figure 7. Break-even price: variant 4 (the least economically beneficial).

The analysis of the results obtained for variant W1 leads us to similar conclusions. Considering expenditures and production volumes, the minimal selling price differs from that derived for variant W4. For variant W1, the break-even price in 2023 falls in the range of 9.02–12.49 EUR/Mg (statistical range 3.47 EUR/Mg), and the variability range of the results is nearly 3 times smaller than in variant W4. The 90% confidence interval yields the price range of 9.56–11.39 EUR/Mg. The model for 2026 shows the range of break-even prices to be 8.78–32.66 EUR/Mg, and the 90% confidence interval becomes 10.87–22.51 EUR/Mg, producing the scatter of 12.14 EUR/Mg.

The statistics of break-even price simulations are summarised in Table 11.

The projected profitability level is the key indicator determining the rationale behind economic planning and commencement of mining operations in line with the given scenario. Potential profit levels in the projected period are simulated for the respective variants of mining operations and are shown in Figures 8 and 9.

Table 11. Simulation of the break-even price of the marketed product for subsequent years of mining operations [EUR/Mg].

	W1	Min	Max	90%	St. d.		W2	Min	Max	90%	St. d.
2023	10.45	8.91	13.36	9.62–11.48	0.56	**2023**	11.79	10.04	15.31	10.84–13.00	0.66
2024	11.88	7.89	19.64	9.73–14.62	1.51	**2024**	13.39	9.07	22.51	11.02–16.43	1.68
2025	13.53	7.78	26.97	10.11–17.91	2.52	**2025**	15.24	8.96	29.87	11.49–20.12	2.78
2026	15.76	7.63	43.61	10.87–22.51	3.72	**2026**	17.73	8.85	48.20	12.39–25.15	4.09

Table 11. *Cont.*

	W3	Min	Max	90%	St. d.		W4	Min	Max	90%	St. d.
2023	13.52	11.50	18.02	12.41–15.04	0.80	**2023**	16.04	13.51	21.56	14.66–17.05	0.99
2024	15.32	10.84	26.47	12.72–18.68	1.88	**2024**	19.18	12.70	31.76	15.03–22.30	2.30
2025	17.37	10.73	32.98	13.34–22.82	3.06	**2025**	20.66	12.57	39.58	15.75–27.24	3.72
2026	20.20	10.74	52.67	14.38–28.55	4.48	**2026**	24.03	12.54	63.67	16.99–34.14	5.43

	W5	Min	Max	90%	St. d.
2023	12.00	10.12	15.75	10.98–13.30	0.70
2024	13.64	9.14	23.28	11.16–16.83	1.76
2025	15.55	9.02	30.83	11.65–20.66	2.91
2026	18.12	8.88	49.91	12.55–25.89	4.27

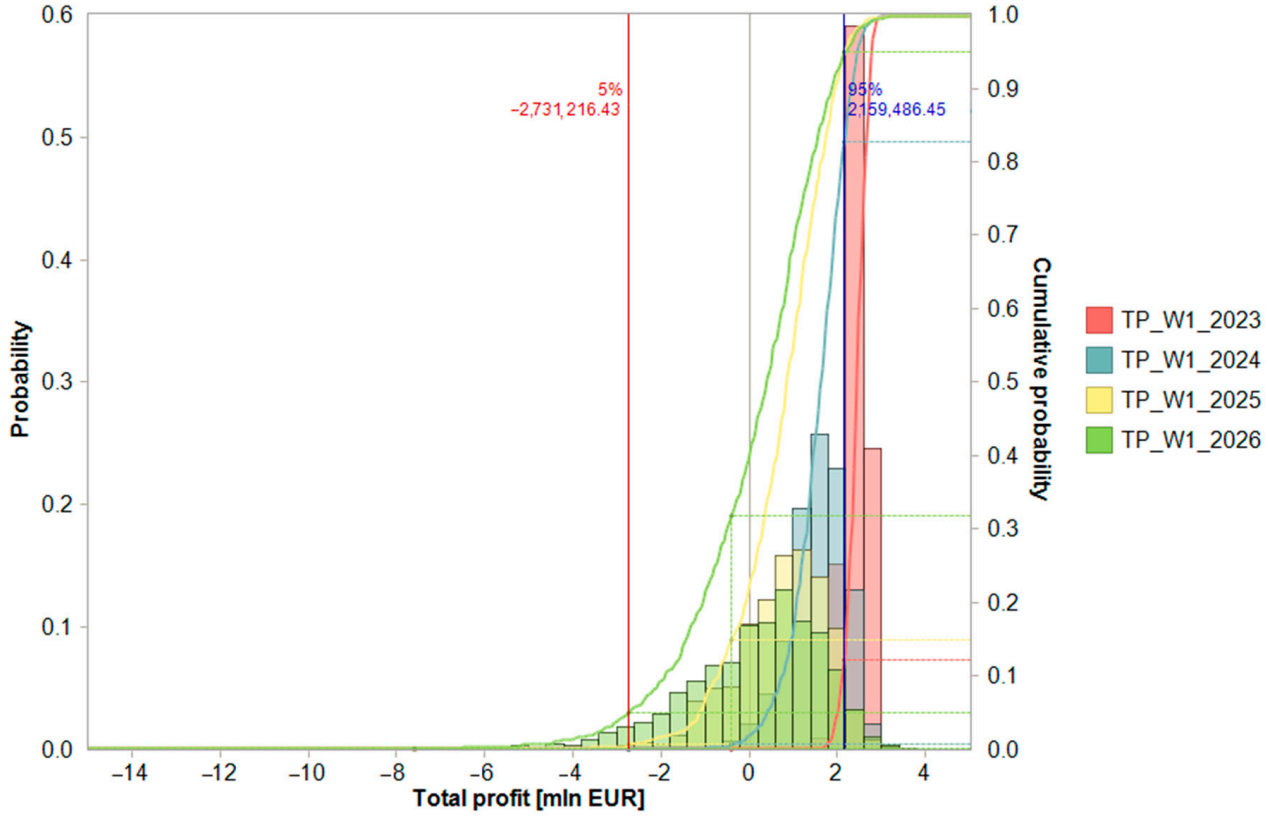


Figure 8. Distribution of profit data for variant W1.

Each simulation model showed decreasing profitability, mostly due to the projected long-term increase in fuel and electricity prices. The actual profit levels depend on the configuration of deployed mining equipment, i.e., on the fuel consumption and electricity demand. The relative share of fuel and electricity prices determines the rate of profit decrease in subsequent years of mining operations, and the variability is due to the differences in mining equipment configurations in the analysed variants (Table 12). The largest decrease in the profit level is reported for variant W4, where the mean profit fell from 0.08 mln to −3.35 mln (the difference being 3.43 mln EUR). As regards the mid-term forecasts, assuming that production costs will increase in line with inflation rates, the decrease in profitability would be the least in variant W4, with a profit decrease of 2.54 mln EUR. This is the variant in which production is found to be profitable throughout the entire analysed period, whilst the modelled probability of a financial loss becomes 0% in 2023, 1% in 2024,

20% in 2025 and nearly 40% in 2026. Despite the variable conditions of minerals and metal on the market and despite fluctuating fuel prices, variant W1 is expected to continue to be profitable for the longest time, mostly due to the specificity of the configuration of mining equipment (the smallest number of deployed machines among the analysed variants) and the shortest haulage distances (the lowest transport costs).

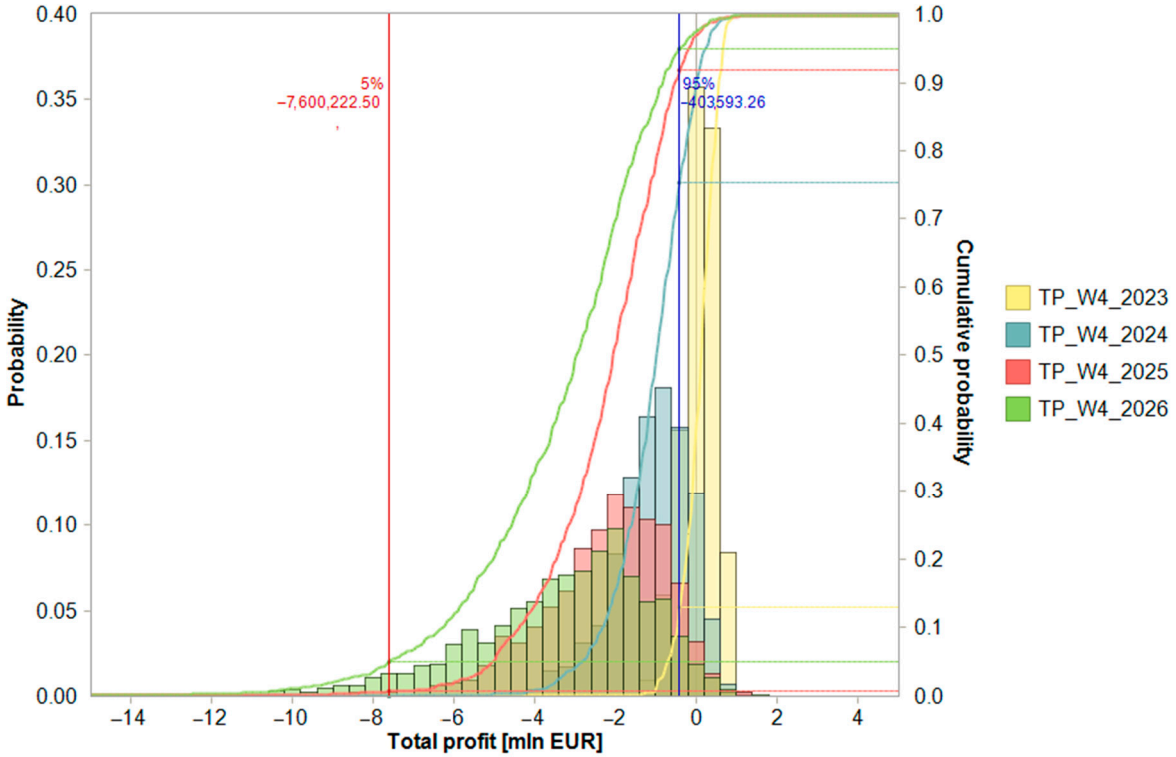


Figure 9. Distribution of profit data for variant W4.

Table 12. Profit simulation data for subsequent years of mining operation for all proposed variants [mln EUR].

	W1					W2			
	Av.	**Min**	**Max**	**90%**		**Av.**	**Min**	**Max**	**90%**
2023	2.42	1.20	3.07	1.99:2.77	**2023**	1.9	0.3	2.5	1.3:2.3
2024	1.56	−1.66	3.23	0.40:2.45	**2024**	0.9	−2.9	2.7	−0.3:1.9
2025	0.72	−4.91	3.1	−1.1:2.2	**2025**	0.01	−6.1	2.6	−2.7:1.5
2026	0.12	−11.5	3.53	−2.7:2.15	**2026**	−0.7	−13.5	3.0	−3.8:1.5
	W3					**W4**			
	Av.	**Min**	**Max**	**90%**		**Av.**	**Min**	**Max**	**90%**
2023	1.18	−0.79	2.07	0.52:1.67	**2023**	0.08	2.24	1.14	−0.72:0.66
2024	0.12	−4.76	2.08	−1.36:1.25	**2024**	−1.09	−6.79	1.21	−2.81:0.24
2025	−0.92	−7.76	1.98	−3.33:0.83	**2025**	−2.27	−10.21	1.13	−5.07:−0.21
2026	−1.81	−16.04	2.32	−5.49:0.73	**2026**	−3.35	−20.00	1.48	−7.60:−0.40

Table 12. *Cont.*

	W5			
	Av.	**Min**	**Max**	**90%**
2023	1.78	0.20	2.56	1.23:2.20
2024	0.82	−3.23	2.71	−0.53:1.86
2025	−0.13	−6.54	26.17	−2.29:1.51
2026	−0.87	−14.22	3.01	−4.14:1.46

4. Conclusions

In this article, we presented a method for calculating the profitability of producing raw materials from specific deposits considering various operational and financial factors. Particular emphasis was placed on the impact of fluctuating prices of energy carriers and the selection of production system configurations with varying energy consumption levels. The key conclusions drawn from the conducted research are as follows:

- The presented method of economic assessment of the deposit extraction enables us to simulate various mining operation scenarios, taking into account the variable operating costs associated with different configurations of mining equipment. The simulation results show forecasts of operating costs, and by incorporating the projected price levels, we can assess the minimum selling price in the next years (in the context of a probability assessment) and the risk of financial loss.
- Long-term planning of mining operations is particularly important for sustainable resource management, as it enables a reduction in the unnecessary transportation of bulk materials. Time series price models for long periods of forecasts will not be a good response due to the general volatility of economic processes and the failure to take discrete economic regulation occurring in successive periods into account. Therefore, the model is only applied for medium-term profitability analysis. Another limitation of these simulation models is the need for detailed information about the actual costs, which is only generally available for existing and operational mining companies. Pre-investment- and investment-stage projects often lack such detailed data.
- Unlike standard analytical models, the proposed simulation model is a valuable tool for generating various scenarios of mining operations, considering production cost variability and assumed profitability levels. The simulation data provide essential information for mine operators making investment decisions, especially during times of fuel and electricity price instability and fluctuating production costs of aggregates—products that are crucial in industries such as construction.
- Key issues include future fuel prices and the steadily increasing cost of electricity in the mid-term range. Interestingly, the most profitable scenario involves using the minimum number of mining machines and maintaining relatively short haulage distances while ensuring predetermined productivity levels. To enhance profitability, a thorough analysis of mining conditions and the business environment is essential. Additionally, selecting modern, environmentally friendly mining equipment can significantly reduce costs and improve profitability.
- The process begins with identifying major cost components and ends with profitability analysis and production planning, considering the potential profit levels that are necessary to sustain business operations. Furthermore, mining companies aim to maximize productivity amid shrinking resources, making such analyses useful tools for the strategic planning of future mining work. There is a growing need to develop and improve analytical tools and simulation models that link data acquisition with the increasing demands of the business world.
- The proposed methodology is universal and applicable to other mining and quarrying companies, regardless of their specific operations. It allows for the selection of an optimal machinery setup for plant operations, taking into account both technological

and economic factors. This simulation model, focused on the economic aspects of exploitation process efficiency, enables the assessment of the profitability of mining production from low-quality deposits with a higher risk of incurring losses. It can be used to evaluate the profitability of mining production not only in the limestone quarry but also in other mining companies, as well as other energy-intensive industries.

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