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Optimizing resource management under variable geological and mining conditions using a longwall advance model

Introduction

Production planning in hard coal mines constitutes a key element of effective resource management, encompassing both the rational utilization of technical infrastructure and the optimization of excavation processes under variable geological-mining conditions.

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These parameters significantly determine the exploitation rate and the viability of production plans. In planning practice, production is often forecasted based on averaged monthly data, which does not reflect the actual variability of the effective working time of the longwall system nor the daily face advance rate, and only to a limited extent accounts for the constraints of the mine's main technological flow (Polak 2014). In the context of deep mining, characterized by high costliness, increased energy consumption, and increasing natural hazards, precise forecasting and planning are essential for maintaining economic viability (Jonek-Kowalska and Turek 2016; Matthee et al. 2024). The high, mining-specific uncertainty and risk, which often prevent the implementation of plans according to their design assumptions, necessitate the systematic collection of as-built data to develop stochastic process characteristics and assess risk (Magda 2008) as well as the application of advanced analytical methods.

Under these conditions, the longwall face advance, understood as the measure of the face's progression over time, becomes one of the key indicators for the efficiency of mine resource management. It determines the level of production capacity utilization and influences energy consumption, exploitation intensity, and the unit cost of extraction. Its maximization, while adhering to operational parameters and work safety standards, translates directly into improved economic and energy efficiency of the mining process. Forecasting this advance rate remains a complex issue, however, due to its strong dependence on technical, organizational, mining, and geological factors (Dyczko et al. 2020). Effective resource management, therefore, requires the decomposition and quantification of these factors. Among them, geological and mining (GM) conditions constitute the primary factor determining operational and exploitation parameters (Sobczyk 2022). This relationship can be described using the OEE (Overall Equipment Effectiveness) indicator, which measures the efficiency of the mine's technical resource utilization, including (Polak 2014):

- Availability – defining the technical and organizational readiness of the longwall system; its fluctuations often stem from unfavourable geological-mining (GM) conditions that affect equipment failure rates and downtime.
- Performance – dependent on the impact of GM conditions on the mining rate, e.g., the necessity of conducting adaptive work in areas of geological disturbances.

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- Quality – related, for example, to the dilution of waste rock in the run-of-mine output, which reduces the efficiency of deposit utilization.

The development of digital technologies in recent years has significantly supported the process of resource management and production planning. MES and SCADA systems enable the acquisition and analysis of operational data in real-time (Polak 2016) while platforms such as MineScape or Deswik allow for the integration of geological models (Golda et al. 2024). This integration is increasingly supported by advanced analytical methods, including machine learning (Krawczyk 2023; Chimunhu et al. 2024) processing and application of spatial data in the mining industry. A comparative study of the evolution of spatial data exchange methods between Geographic Information Systems (GISs). Simultaneously, research on the assessment of risk and the arduousness of exploitation conditions (Sobczyk and Kopacz 2018; Galica 2023; Sobczyk et al. 2024) indicates the need to combine multi-criteria methods (e.g., AHP) with spatial data analysis, which allows for a better assessment of production potential and the risks associated with resource utilization.

Analyses of mining performance (Kalinin et al. 2019; Khorolskyi et al. 2019; Sobczyk et al. 2020; Snopkowski et al. 2025) are often based on mass-based indicators (tonnage per unit of time), which combine advance with geological-geometric parameters of low variability into a single metric. A frequent primary objective is to determine the influence of geomechanical conditions on excavation stability, which is a prerequisite for continuous and safe exploitation advance (Yetkin et al. 2024). In a similar geomechanical context, the works of Vlasov et al. (2022). Aghababaei et al. (2019) forecasted longwall advance using the RES methodology (which serves to quantify interactions) based on seven parameters; their analysis was limited to the conditions of six longwall panels in a single mine and only seven geological-mining factors. In such research, coal seam models have also been utilized (Okol'nishnikov et al. 2021).

In this paper, a less common approach was adopted, focusing on modelling the longwall advance itself to analyze the influence of a broad spectrum of GM parameters obtained from deposit modelling, three-dimensional production planning, and monitoring systems. The longwall advance was treated as an independent and primary process parameter. It should be noted that run-of-mine tonnage (both gross and net) is a derivative (composite) parameter, resulting from the advance rate and local geometric (gate height) and geological (share of partings, out-of-seam dilution) characteristics, which are often measured less frequently or are based on aggregate production measurements. This approach enables the direct linking of the advance rate with spatial geological and technical data, which facilitates resource management optimization, improves planning efficiency, and also allows for the identification of mining process bottlenecks.

Within the broader context of the proposed methodology (Figure 1), the advanced model constitutes a key element of an integrated deposit management and production planning system, based on the digital deposit model as the data source for the geological and structural conditions of the deposit seams. This data feeds into mine design and scheduling models; the results of such a constrained schedule are then verified against the limitations of the mine's

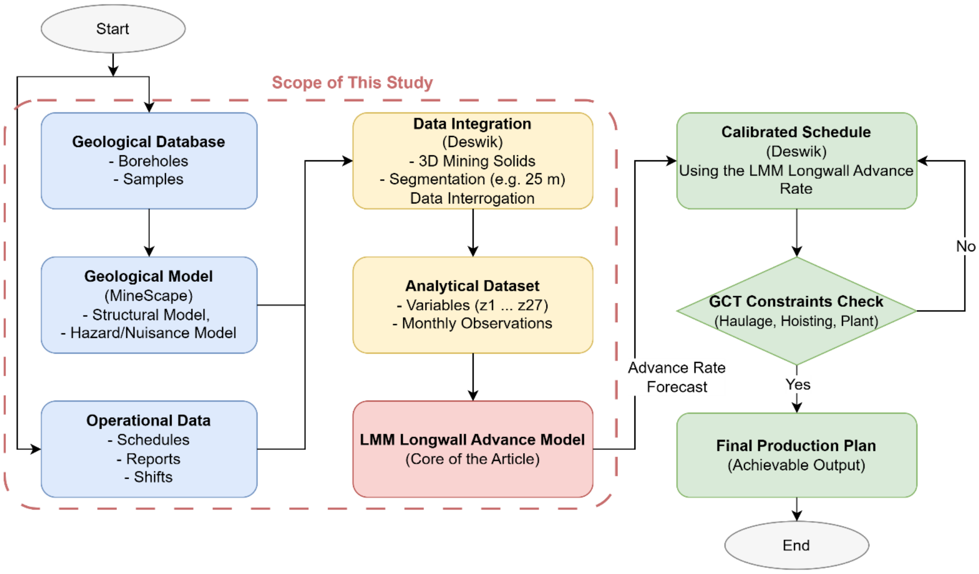

Fig. 1. Schematic of the proposed methodology for integrated production planning, highlighting the scope of the current study

Rys. 1. Schemat proponowanej metodyki zintegrowanego planowania produkcji z zaznaczeniem zakresu niniejszej pracy

main production chain (GCT). Thus, a precise diagnosis of bottlenecks is possible, replacing "expert" estimates with a data-driven approach.

The main goal of this study was to create a mathematical (statistical) model that could predict the advance of the longwall face in changing geological and mining conditions. This model is intended to be both a practical forecasting tool and an aid in decision-making for mine planning. By accurately predicting whether production plans are achievable, taking into account local geology, technology, organization, and natural risks, this approach supports better planning and use of resources in hard coal mining. The model, together with its validation and statistical evaluation, is described in detail in Section 2.

1. Data and methodology

1.1. Data sources and integration

The research material consisted of geological, mining, and production data from three hard coal mines (designated in the article as Mine 1, Mine 2, and Mine 3), located in the Upper Silesian Coal Basin. The analysis covered 47 longwall panels in 17 seams exploited at these mines over the past 5 years. Data sources encompassed digital geological models, 3D models of mining workings, as-built production schedules, and operational data.

The primary source of information regarding geological conditions and natural hazards was the digital geological deposit models developed in the MineScape software. For each mine (Table 1), these models consisted of:

1. A structural model (Figure 2), describing the seam geometry and discontinuous tectonic deformations (faults) with a throw greater than half the seam thickness.
2. A map of smaller faults (with a throw not exceeding half the seam thickness) – due to their large number, these faults were not included in the surface modelling and were only used to calculate the fault indicator.
3. A quasi-parameter model, quantifying the spatial distribution of natural hazards (e.g., methane, rockbursts, gas and rock outbursts, spontaneous combustion tendency) and other difficulty factors.

Table 1. Characteristics of deposit models for individual mines

Tabela 1. Charakterystyka modeli złoża dla poszczególnych kopalń

Mine	Model area (km^2)	Total number of modeled seams		Number of modeled faults
		modelled seams	mineable seams	
Mine 1	18.2	39	23	76
Mine 2	36.1	41	18	29
Mine 3	21.6	18	8	49

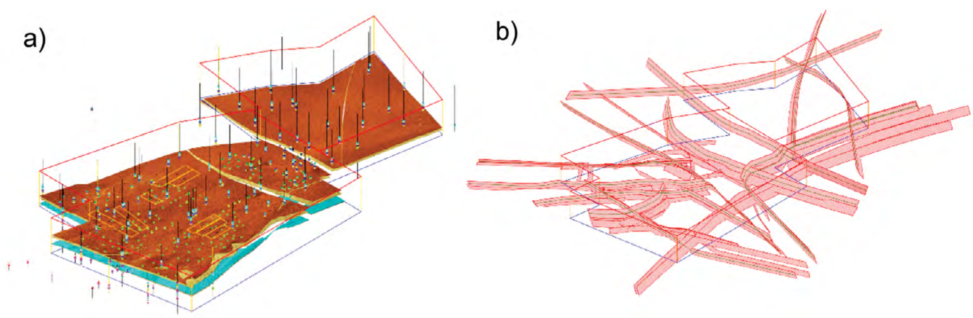

Fig. 2. Deposit model visualizations of Mine 2
a) location of the analysed longwall panels against the background of the seam floor, boreholes, and roadway profiles; b) surfaces of major faults modelled within the deposit

Rys. 2. Wizualizacje modelu złoża Kopalni 2
a) lokalizacja analizowanych paneli ścianowych na tle spągu pokładu, otworów wiertniczych i profili wyrobisk; b) powierzchnie głównych uskoków zamodelowanych w obrębie złoża

The geological models were imported into the Deswik mine planning and scheduling software. Within this environment, the longwall panels (as 3D solids) for the analyzed period were modelled (Kopacz et al. 2020). A key step in the procedure was to divide each longwall solids into segments of a constant length (25 meters of advance). This segmentation, which is also used in the planning process, serves to preserve the local variability of analyzed parameters at a resolution appropriate for the monthly time step. Subsequently, through a geological model interrogation process, values for geological parameters (Figure 3) and natural hazards were sampled for each segment directly from the MineScape digital deposit model.

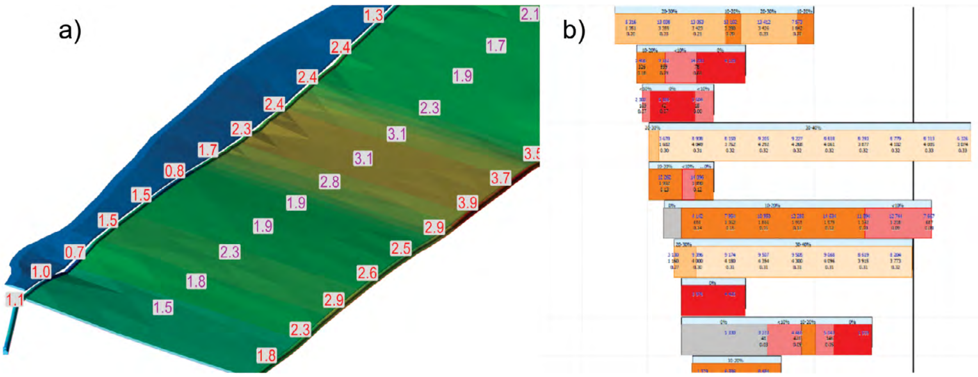

Fig. 3. Visualizations of the model and schedule for Mine 2
a) example longwall from Mine 2 with segments colored according to the percentage of partings in seam;
b) excerpt from the schedule of longwall workings

Rys. 3. Wizualizacje modelu i harmonogramu dla Kopalni 2
a) przykładowa ściana z Kopalni 2 z segmentami pokolorowanymi według procentowego udziału przerostów w pokładzie; b) fragment harmonogramu robót ścianowych

The operational (production) dataset included the actual monthly face advance and number of shifts, derived from as-built schedules, SCADA data, and dispatch system reports, and was then matched with the modelled geological and hazard data for each longwall in monthly intervals (Figure 3).

1.2. Analytical dataset

After integrating all sources, the data were standardized to a common monthly interval. Each observation in the dataset represents a single month of operation for a specific longwall panel. The choice of the month as the basic analytical unit was dictated by the characteristics of mining data; data acquired at short intervals (shift or daily) are characterized by very high variability and randomness, resulting from numerous disruptions, failures, and the uncertain work environment. The monthly period, during which formal production reconciliation and

Table 2. Characteristics of variables included in the analysis

Tabela 2. Charakterystyka zmiennych uwzględnionych w analizie

Variable symbol	Full variable name	Variable group	Data type (Unit)
z1	Mine	Identification (grouping)	Text
z2	Seam name	Identification (grouping)	Text
z3	Mining crew/team	Identification (grouping)	Text
z4	Longwall panel name	Identification (grouping)	Text
z5	Month number	Temporal (categorical)	Numerical (–)
z6	Seam exploitation sequence in the mine	Geological	Numerical (–)
z7	Seam group	Geological	Numerical (–)
z8	Coal share in gate height	Geological	Numerical (–)
z9	Gate height	Mining-related	Numerical (m)
z10	Share of partings in seam thickness	Geological	Numerical (–)
z11	Share of roof/floor dilution in gate height	Mining-related	Numerical (–)
z12	Transversal inclination (panel width direction)	Mining-related	Numerical (°)
z13	Longitudinal inclination (advance direction)	Mining-related	Numerical (°)
z14	Longwall panel width	Geological	Numerical (m)
z15	Mining depth	Geological	Numerical (m)
z16	Dist. from the materials and man-riding shaft	Mining-related	Numerical (m)
z17	Fault indicator (tectonic disturbance index)	Geological	Numerical (–)
z18	Share of start-up or completion stage	Mining-related	Numerical (–)
z19	Gas/dust outburst hazard level	Natural hazards	Numerical (–)
z20	Spontaneous combustion tendency	Natural hazards	Numerical (–)
z21	Rockburst hazard level	Natural hazards	Numerical (–)
z22	Distance from panel ends	Mining-related	Numerical (m)
z23	Share of production shifts	Organizational	Numerical (–)
z24	Roof rock class	Geological	Numerical (–)
z25	Rock mineability class	Geological	Numerical (–)
z26	Previous mining influence	Mining-related	Numerical (–)
z27	Longwall advance per shift with production	Dependent variable	Numerical (m/shift)

geodetic measurements occur, averages out these short-term fluctuations, providing a stable and reliable picture of the underlying relationships, which is essential for modelling the impact of geological and mining conditions. This also represents a compromise between model fidelity and computational feasibility, particularly in strategic planning (Newman et al. 2010).

The variable selection process began with an initial list of 71 variables describing, among others, organizational aspects, run-of-mine quality, and planning conditions, which were obtained from integrated data reporting within the Deswik software. After eliminating variables that were highly correlated or carried redundant information, 30 variables remained. Subsequently, three specific hazard variables (Methane hazard categories, Coal dust hazard class, and Water hazard degree) were removed. This outcome is primarily attributed to these categories exhibiting very low variability within the analyzed dataset, although it is acknowledged that these variables can have a significant impact under specific conditions (Szlązak and Kubaczka 2012). This multi-stage refinement yielded the final analytical dataset, in which each observation corresponds to a monthly operational period of a given longwall. As detailed in Table 2, this dataset consists of 27 variables, defined as 26 independent variables (predictors describing mining difficulty) and one dependent variable (longwall advance per production shift).

The explained (dependent) variable in the model is z27 – Longwall advance per shift with production. This variable was selected from 4 possible options as a result of the analysis described in Section 1.3. It is calculated by dividing the total monthly advance (in meters) for each longwall by the number of production shifts. Each observation thus represents the average advance per shift achieved on a specific longwall during one month. This method of data normalization (by the number of shifts, rather than days) allows the model to be independent of variable work organization (such as a varying number of production shifts per month).

The analyzed dataset consisted of 607 observations (longwall-months), free of missing values in the included variables. These variables were divided into five groups: z1–z4 (identification and grouping variables: Mine, Seam name, Mining crew/team, Longwall panel name), z5 (temporal (categorical) variable: Month number), z6–z26 (numerical predictors: geological, mining-related, organizational, and natural hazard variables), and z27 (dependent variable). Some categorical (ordinal) variables were converted into numerical form so that they could function as destimulants (such as natural hazards variables, Rock mineability class and Previous mining influence) or stimulants (Roof rock class) in the analysis. In this respect, an approach consistent with the methodology for quantifying the arduousness of geological-mining conditions was adopted (Sobczyk 2022).

1.3. Exploratory data analysis

Exploratory data analysis (EDA) was performed to understand data structure and relationships (Figure 4–7).

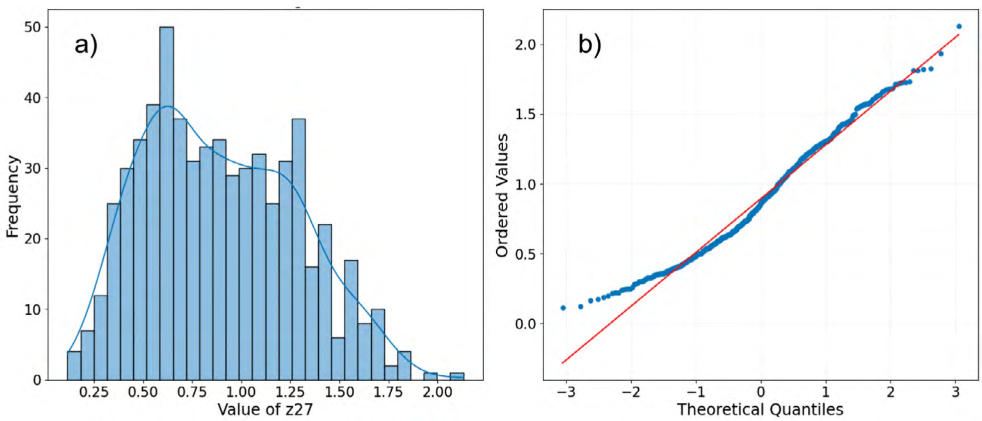

Fig. 4. Histogram of the dependent variable z27 (a)
and Quantile-Quantile (Q-Q) plot against a normal distribution (b)

Rys. 4. Histogram zmiennej zależnej z27 (a)
oraz wykres kwantylowy (Q-Q) względem rozkładu normalnego (b)

Figure 4 presents visual diagnostics for the dependent variable z27 (Longwall advance per shift). The histogram (Figure 4a) suggests an approximately unimodal distribution with slight positive skewness (0.34). The Quantile-Quantile (Q-Q) plot against a normal distribution (Figure 4b) shows reasonable alignment of the points along the reference line, indicating approximate normality, although minor deviations are present in the tails. It should be noted that this histogram, like those in Figure 5, is based on raw monthly data (N = 607) and thus reflects the relative number of monthly data points; panels with a longer operational time contribute more records to this distribution. The mean value of z27 is 0.89, and the standard deviation is 0.39, with observed values ranging from 0.11 to 2.13.

Histograms showing the distributions of selected key independent variables used in the exploratory analysis (Figure 5). The variables exhibit diverse distributional shapes. Some, originally representing categories or ordinal scales (z7, z20, z21, z24, z26) but treated numerically here, often show distinct peaks corresponding to these underlying groups and reflecting the discrete nature of the original grouping. Other variables, more inherently continuous, also vary: z8 – Coal share in gate height demonstrates left-skewness (–0.8), suggesting a tendency towards higher coal content with fewer instances of very low content. Conversely, a variable like z17 – Fault index shows strong right-skewness (4.5) and high kurtosis (35.9), indicating that most observations have low values but there are infrequent occurrences of very high values. While these distributions deviate from normality, this is common in real-world data, suggesting the chosen analytical method should be robust to such characteristics.

Boxplots comparing the distribution of z27 across the different mines (z1) (Figure 6) reveal differences in central tendency and variability. For example, Mine 3 shows the highest median value (1.30), while Mine 1 shows the lowest (0.67). The interquartile range (IQR) also varies, indicating different levels of within-mine variability (e.g., 0.47 for Mine 2, 0.35 for Mine 3). These visual differences support the inclusion of random intercepts for "z1" in the LMM to account for this group-level variation.

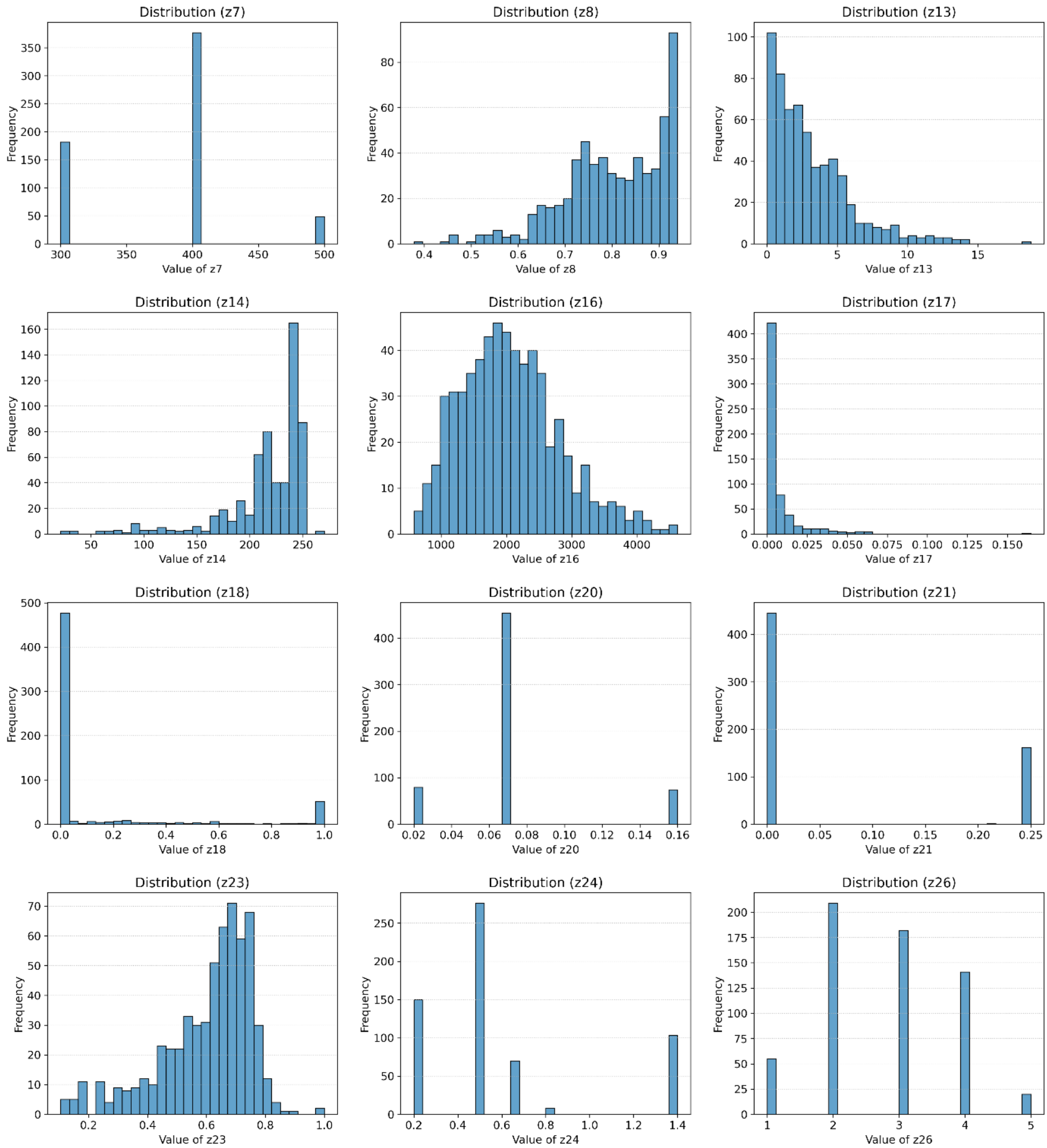

Fig. 5. Histograms of selected independent variables

Rys. 5. Histogramy wybranych zmiennych niezależnych

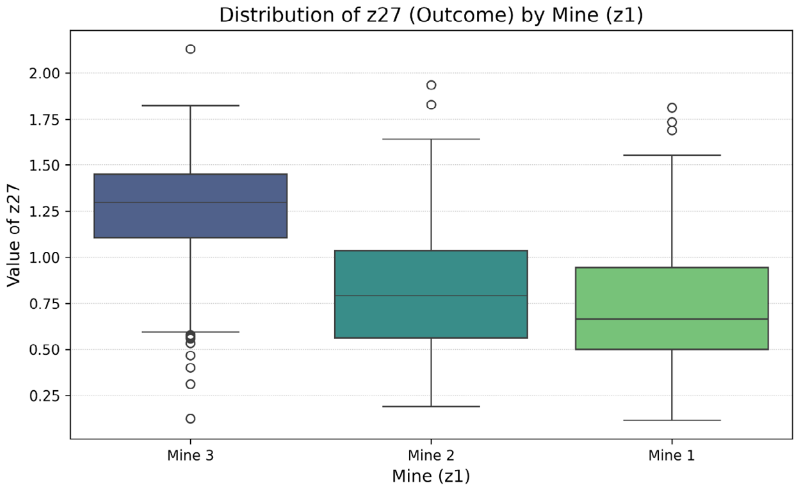

Fig. 6. Distribution of z27 (Advance per shift with production) by Mine (z1)

Rys. 6. Rozkład zmiennej z27 (Postęp na zmianę z produkcją) w podziale na kopalnie (z1)

Additionally, the relationships among the individual variables are presented in the form of an integrated Spearman's rank correlation matrix (Figure 7). It reveals relationships between the numerical independent variables (z6–z26) and the dependent variable (z27). The strongest positive correlations with z27 were observed for z23 (ρ = 0.50) and z15 (ρ = 0.35). The strongest negative correlations were observed for z26 (ρ = –0.34) and z13 (ρ = –0.32). High correlation was also noted between predictors, for instance, between z6 and z7 (ρ = 0.81), suggesting potential multicollinearity addressed later in the Variance Inflation Factor (VIF) analysis.

1.4. Statistical modelling methodology

Selection of the dependent variable

A significant element of the analysis was the selection of the dependent (explained) variable. Several variants of the "longwall face advance" variable were available in the initial dataset:

1. Longwall face advance per shift with production – the most general category, encompassing all elements of the work schedule during which longwall face advance occurred.
2. Longwall face advance per non-maintenance production shift – pertaining to advance during production periods, excluding maintenance shifts (approximately 1/4 of the source information).

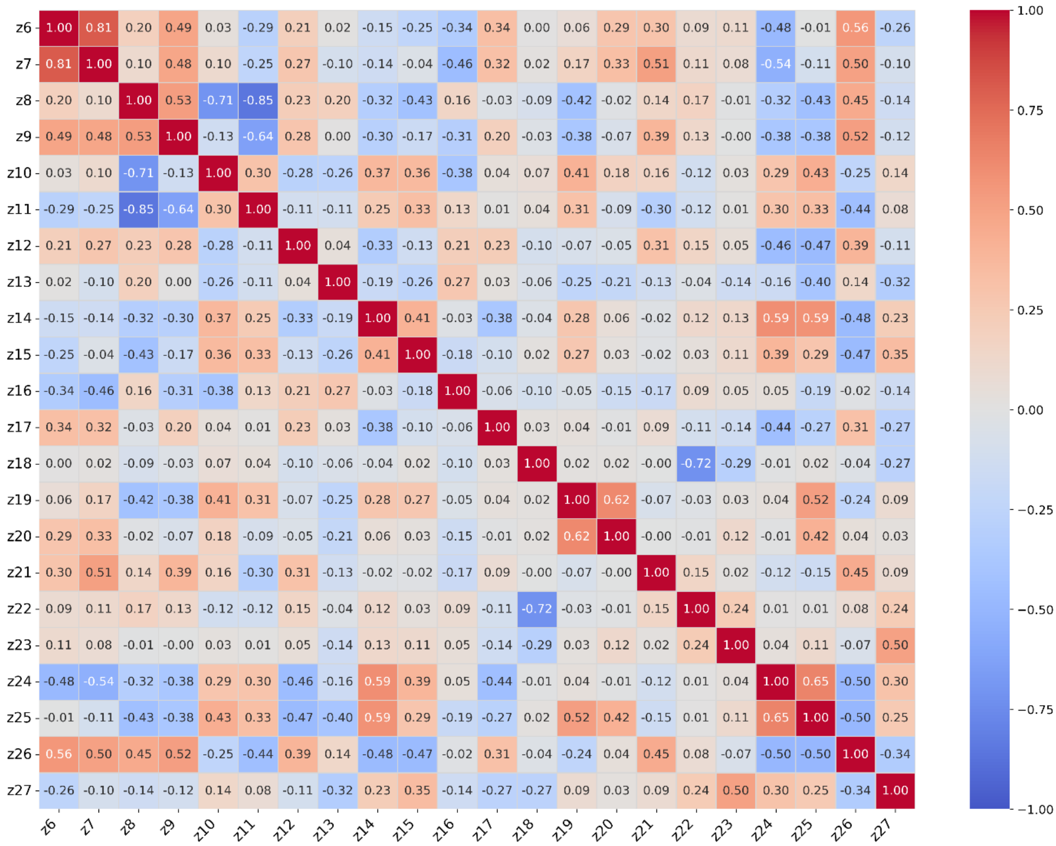

Fig. 7. Spearman correlation matrix for independent variables (z6–z26) and the dependent variable (z27)

Rys. 7. Macierz korelacji rangowej Spearmana dla zmiennych niezależnych (z6–z26) i zmiennej zależnej (z27)

3. Longwall face advance per production shift with production continuity, additionally removing observations following periods of long stoppages.
4. Longwall face advance per non-maintenance production shift with production continuity, a combination of variants 2 and 3.

A preliminary assessment of the different advanced measures (conducted using LMMs) revealed that option 1 (variable z27), in the context of the available set of potential predictors, offered the best prognostic potential. As this initial comparative analysis constituted only an ancillary topic, its detailed results are not documented in this paper.

Statistical modelling

To quantitatively assess the impact of geological-mining and operational factors (variables z5–z26) on z27, linear mixed models (LMMs) were employed. The choice of this model class was motivated by several factors: its relatively intuitive nature, good predictive properties, and, crucially, the hierarchical (nested) structure of the available data. The LMM approach allows not only for evaluating the influence of individual independent variables but also for incorporating the specifics of the data grouping (e.g., mines, seams), which is highly relevant for the practical application of the model in estimating longwall advance under specific operational conditions (Bates et al. 2015).

The necessity of using LMMs arose from the violation of the standard linear regression assumption requiring observation independence. In the analyzed dataset, observations (monthly advance rates) originating from the same mine (z1), the same seam (z2), and potentially also the same mining team (z3) or longwall face (z4), exhibit a natural interdependence – they are more similar to each other than observations from different groups. Linear mixed models explicitly account for this grouping structure by introducing random effects (e.g., for mine and for seam within mine), which allows for obtaining more accurate and unbiased estimates of the influence of the analyzed factors (fixed effects).

The analyses were conducted using a hybrid analytical environment. The primary operational environment was Google Colab, utilizing the Python 3 programming language. It was used for data import, cleaning, merging, and final diagnostics and visualization of results. For the LMM modelling itself, the pymer4 library was used, serving as a Python interface to the R environment. Several R libraries were employed, such as MuMIn, lme4, lmerTest, textreg, scales, and performance (R Core Team 2024). The selection of the best model via the dredge function (Bartoń 2025) was performed in the RStudio (version 2024.04.2) environment, utilizing parallel computation (the parallel package), which significantly reduced the analysis time.

The LMM structure was defined as follows:

- The predictor variables (z5–z26) were treated as fixed effects, representing the factors whose influence on longwall advance (z27) was estimated.
- Variable z5 – Month number was included as a categorical predictor C(z5) to account for potential seasonality.
- The hierarchical grouping structure of the data, based on z1–z4 variables, was incorporated via random effects.

A standard linear model (LM) without random effects was deemed insufficient, as preliminary analyses confirmed it yielded poor predictive performance, being unable to account for the significant baseline variance between mines. After testing various levels of complexity, including models with four (1 | z1 / z2 / z3 / z4) and three (1 | z1 / z2 / z3) levels of nesting, which proved unstable and led to singularity issues, the structure (1 | z1 / z2) was adopted as optimal and stable. This means the model estimates a random intercept (offset) for each mine (z1) and a separate random intercept for each seam (z2) nested within that mine.

Models incorporating random slopes (allowing the effect of predictors to vary by mine) were also considered. However, the random intercept model was intentionally chosen, as it aligns with the study's objective: to quantify the universal (fixed) impact of geological-mining factors across the region, while isolating the specific organizational and infrastructural differences of each mine in the random intercept. This approach provides the best balance of model fit, stability, and interpretability for implementation in planning tools.

The model containing the full set of predictors for z27 was implemented according to the following R command:

$$Model1 \leftarrow lm(lm1 \leftarrow lmer(\mathrm{z27} \sim \mathrm{C(z5)} + \mathrm{z6} + \mathrm{z7} + \mathrm{z8} + \mathrm{z9} + \mathrm{z10} + \mathrm{z11} + \mathrm{z12} + \mathrm{z13} +$$

$$+ \mathrm{z14} + \mathrm{z15} + \mathrm{z16} + \mathrm{z17} + \mathrm{z18} + \mathrm{z19} + \mathrm{z20} + \mathrm{z21} + \mathrm{z22} + \mathrm{z23} + \mathrm{z24} + \mathrm{z25} + \mathrm{z26} +$$

$$+ (1 \mid \mathrm{z1/z2}), na.action = na.fail, data = dane, REML = \mathrm{FALSE})$$

The selection process for the optimal predictive model involved three stages:

1. Collinearity analysis: First, an LMM with the (1 | z1 / z2) random structure was fitted, containing the full set of 22 considered predictors (z5–z26). Analysis of the Variance Inflation Factor for this model revealed strong collinearity among variables z8, z10, and z11. To ensure estimate stability and clear interpretation, variables z10 (Share of partings in seam thickness) and z11 (Share of roof/floor protrusions in gate height) were removed from further analysis, retaining z8 (Coal share in gate height), which was considered the most direct measure of mined material quality, possessing the best measurement quality and interpretability.
2. Heuristic variable pre-selection (p-value): In the second step, the LMM (1 | z1/z2) was refitted using the reduced set of predictors (after removing z10 and z11). Subsequently, to optimize the final, computationally intensive selection stage (dredge), a heuristic based on statistical significance was applied. To reduce the computational burden of the next stage, a preliminary predictor selection was performed, retaining those variables from the refitted model whose p-value was less than a conventionally broad threshold of 0.3. This approach was intended to minimize the risk of prematurely excluding potentially relevant variables that might show significance in combination with others. Only the 15 variables selected in this manner qualified for the final stage.
3. AIC-based selection (dredge function): In the third and final step, the dredge() procedure (from the *MuMIn* package) was applied to the subset of predictors identified in stage 2. This function tested all possible combinations (32,768) of these predictors within the LMM (1 | z1/z2) framework, comparing the resulting models using the Akaike information criterion (AIC). The model characterized by the lowest AIC value was selected as the final model (Figure 8).

The final selected model underwent detailed validation and diagnostics. The LMM assumptions (normality of residuals and homoscedasticity) were assessed graphically (Figure 9a). Potential outliers were examined using standardized residuals and leverage values. Given the inherent high variability of mining data, no observations were removed, as the identified outliers were considered plausible operational events, not measurement errors.

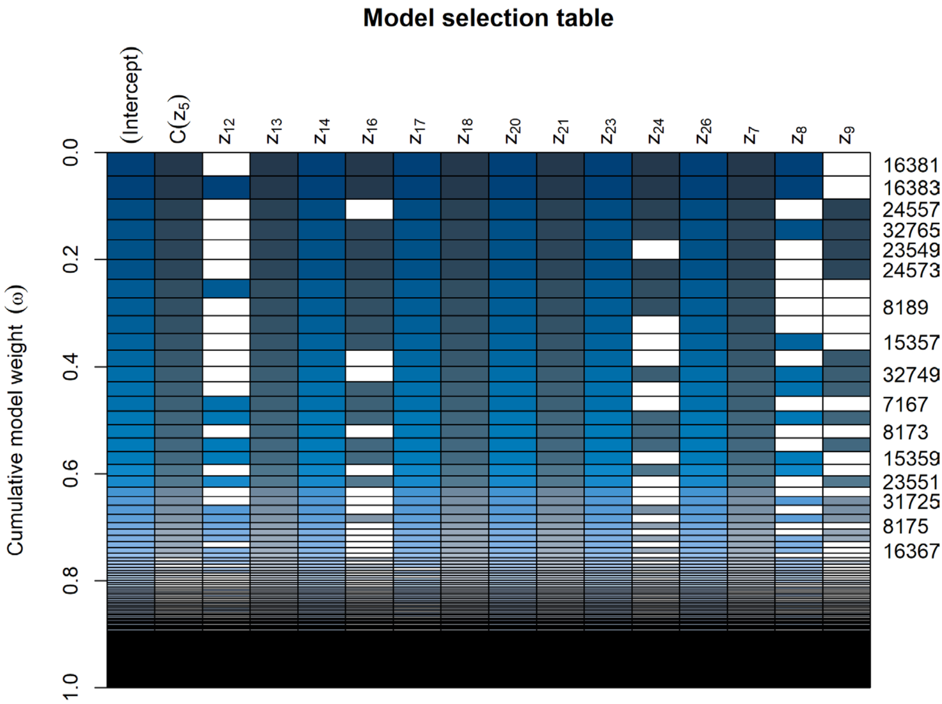

Fig. 8. Model selection plot for z27 based on AIC.
The best model did not include variables z12 and z9 from the 15 pre-selected variables

Rys. 8. Wykres selekcji modelu dla z27 oparty na AIC.
Najlepszy model, wybrany spośród 15 wstępnie wyselekcjonowanych zmiennych, nie uwzględniał z12 i z9

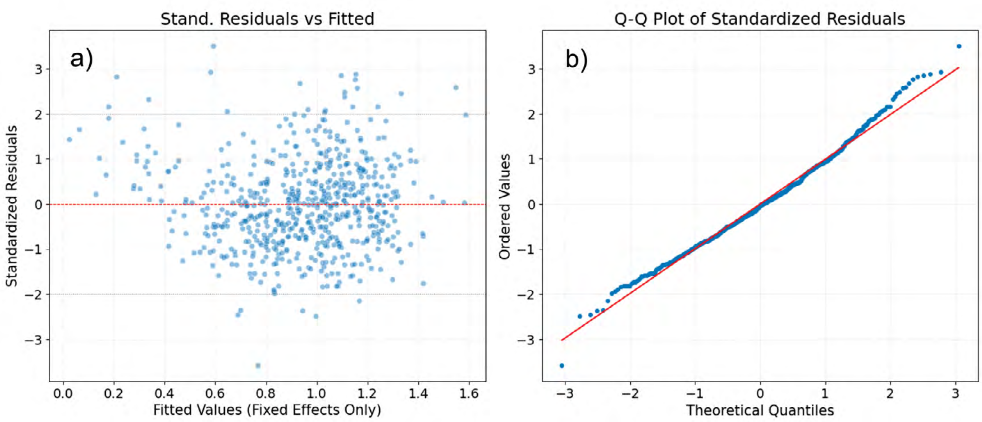

Fig. 9. Diagnostic plots for assessing residual assumptions of the final LMM
a) standardized residuals vs. fitted values (m/shift); b) normal Q-Q plot of standardized residuals

Rys. 9. Wykresy diagnostyczne do oceny założeń resztowych końcowego modelu LMM
a) standaryzowane reszty vs. wartości dopasowane (m/zmianę);
b) wykres Q-Q normalny dla standaryzowanych reszt

Residual diagnostic plots (Figure 9b) support the model's assumptions regarding linearity, homoscedasticity, and normality. The residuals vs. fitted values plot shows a random scatter around zero, indicating linearity and homoscedasticity are reasonably met, despite a few potential outliers. The Q-Q plot confirms that the residuals are approximately normally distributed, with slight deviations in the tails and the presence of two outliers, both of which are deemed acceptable considering the model type and sample size.

To assess the strength of the random effects, the intraclass correlation coefficient (ICC) was calculated, indicating the proportion of the total residual variance in longwall advance attributable to the grouping structure (i.e., observation within specific mines and seams-within-mines). Model fit was evaluated using marginal R-squared (R^2m), which represents the variance explained by the fixed effects alone, and conditional R-squared (R^2c), which represents the variance explained by both the fixed and random effects combined.

2. Modelling results

The application of the model selection procedure led to the identification of the best LMM:

$$z27 \sim C(z5) + z7 + z8 + z13 + z14 + z16 + z17 + z18 + z20 +$$

$$+ z21 + z23 + z24 + z26 + (1 \mid z1 / z2)$$

A comparison between the initial full model (containing all predictors after VIF reduction) and the final model selected via the AIC criterion revealed a significant improvement. As presented in Table 3, the final model exhibits a considerably lower AIC value (59.84) compared to the full model (69.13), confirming the selection of a more parsimonious model while maintaining adequate explanatory power (Table 3).

The model fit assessment revealed that the selected predictors (fixed effects) effectively explain a considerable portion of the variability in longwall advance. The marginal R-squared R^2m, describing the proportion of variance explained solely by the fixed effects, was 0.43.

Table 3. Model comparison summary

Tabela 3. Podsumowanie porównania modeli

Model	k	AIC	LogLik	Delta AIC
Final selected model	27	59.84	–2.92	–
Initial full model	34	69.13	–0.57	9.29

k – Number of estimated parameters, AIC – Akaike Information Criterion, LogLik – Log-Likelihood, Delta AIC – Difference in AIC relative to the best model.

Concurrently, the conditional R-squared R^2c, which accounts for both fixed and random effects (mine and seam), reached a value of 0.64, which accounts for both fixed and random effects (mine and seam membership). This substantial difference between R^2m and R^2c (amounting to 0.21) demonstrates that the grouping structure of the data (random effects) is crucial for understanding the variability in longwall advance rates.

Detailed estimation results for the fixed effects in the final model (excluding the categorical variable C(z5) are presented in Table 4 and Figure 10. This table combines the coefficient estimates, their standard errors (SE), results from significance tests (t-statistics and p-values), and the overall effect significance (Type III ANOVA F-test, Figure 11).

Table 4. Fixed effects estimates (excluding C(z5))

Tabela 4. Oszacowania efektów stałych (z wyłączeniem C(z5))

	Estimate	SE	df	t	Pr(> |t|)	F value	Pr(>F)
(Intercept)	1.4959	0.2369	29	6.3149	<.0001	–	–
z7	–0.0014	0.0005	14	–2.9508	0.0102	8.7075	0.0102
z8	0.2014	0.1249	112	1.6121	0.1098	2.5987	0.1098
z13	–0.0206	0.0043	241	–4.7458	< 0.0001	22.5229	<0.0001
z14	–0.0024	0.0004	118	–6.5919	<0.0001	43.4536	<0.0001
z16	–0.0000	0.0000	168	–1.8794	0.0619	3.5321	0.0619
z17	–2.2650	0.8606	540	–2.6320	0.0087	6.9276	0.0087
z18	–0.3035	0.0367	603	–8.2706	<0.0001	68.4032	<0.0001
z20	2.8195	0.5454	23	5.1698	<0.0001	26.7269	<0.0001
z21	0.5985	0.1378	286	4.3440	<0.0001	18.8701	<0.0001
z23	0.8983	0.0741	599	12.1281	<0.0001	147.0916	<0.0001
z24	0.0782	0.0471	77	1.6609	0.1008	2.7586	0.1008
z26	–0.0924	0.0176	117	–5.2407	<0.0001	27.4648	<.0001

Estimate – estimated coefficient, SE – Standard Error, df – degrees of freedom, t – t-statistic, Pr (> |t|) – p-value for t-test, F value – ANOVA F-statistic, Pr (>F) – p-value for F-test.

The model identified 9 variables as statistically significant ($p < 0.05$) predictors of longwall advance (colored in red in Table 4). The variables z13 – Longitudinal inclination, z14 – Longwall panel width, z17 – Fault indicator, z18 – Share of start-up or completion stage, z26 – Previous mining influence, and z7 – Seam group exhibited a statistically significant negative impact (inhibiting longwall advance). As expected, an increase in geological-mining complexity (such as z17 – Fault indicator and z26 – Previous mining influence)

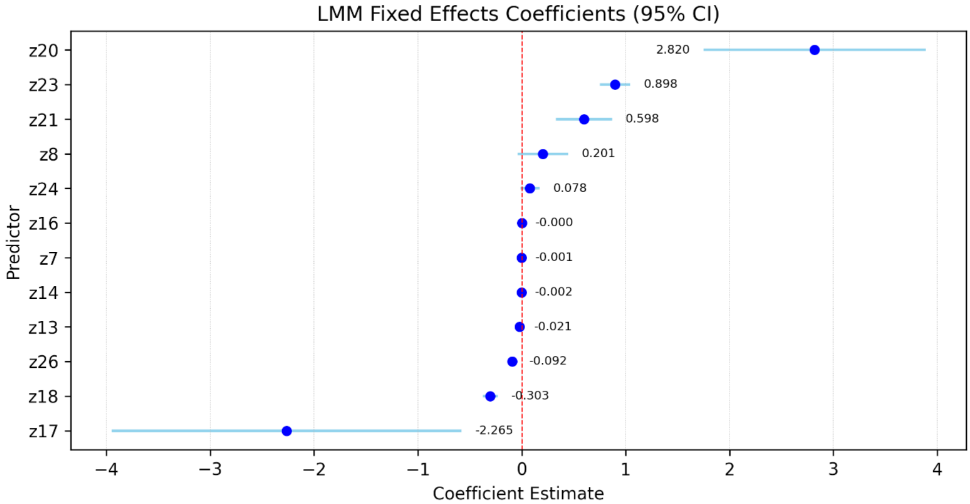

Fig. 10. LMM fixed effect estimates for z27 with 95% confidence intervals

Rys. 10. Oszacowania efektów stałych LMM dla z27 z 95-procentowymi przedziałami ufności

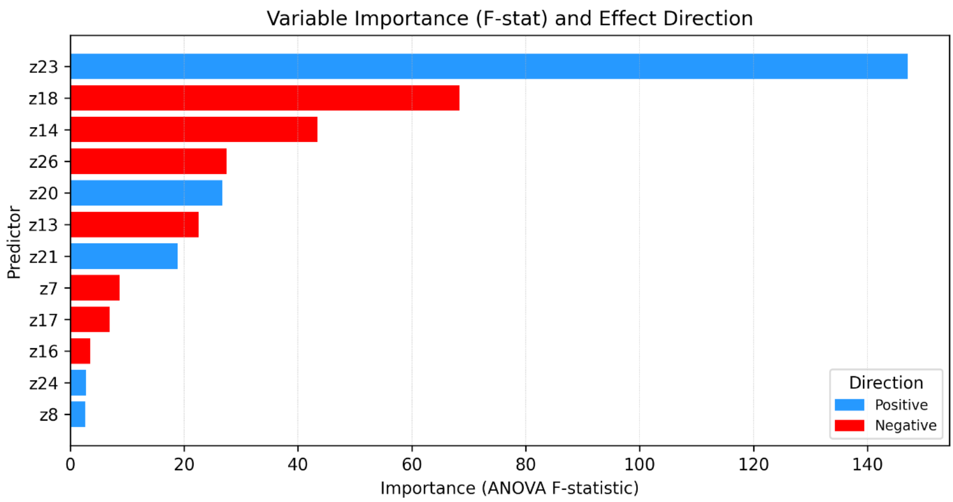

Fig. 11. Ranking of predictor importance (ANOVA F-statistic) and direction of effect on z27

Rys. 11. Ranking ważności predyktorów (statystyka F ANOVA) i kierunek wpływu na z27 as well as increased geometric dimensions (z14 – Longwall panel width) or complexity (z13 – Longitudinal inclination) is associated with lower longwall advance per shift. The variable z18 (Share of start-up or completion stage) showed an exceptionally strong negative impact, confirming that the start-up and completion phases are significantly less efficient than the stable exploitation phase.

A statistically significant positive effect (increasing longwall advance) was observed for the organizational variable z23 – Share of production shifts, which was identified as the strongest predictor in the model (highest F-statistic). This indicates that a greater share of production shifts (production continuity) correlates with higher advance per unit shift, potentially creating a positive feedback loop where efficient, continuous operation reinforces itself. Interestingly, the hazard variables z20 – Spontaneous combustion tendency and z21 – Rockburst hazard level also exhibited a significant positive effect. A proposed explanation for this counterintuitive finding is presented in Section 3.

Analysis of the temporal variable C(z5) – Month number revealed overall statistical significance, indicating the presence of seasonality in the z27. Detailed results show that, compared to the reference month (January), significantly lower advance ($p < 0.05$) is achieved during the summer months (July–September), corresponding to levels C(z5)7 to C(z5)9 (coloured in red in Table 5).

Table 5. Fixed effect estimates for C(z5) (Month number)

Tabela 5. Oszacowania efektów stałych dla C(z5) (Numer miesiąca)

	Estimate	SE	df	t	Pr (> |t|)	F value	Pr (>F)
C(z5)1 (Ref)	0.0000	–	–	–	–	2.4068	0.0063
C(z5)2	–0.0078	0.0476	581	–0.1638	0.8699	–	–
C(z5)3	–0.0762	0.0469	583	–1.6254	0.1046	–	–
C(z5)4	–0.0756	0.0466	583	–1.6225	0.1052	–	–
C(z5)5	–0.0712	0.0460	585	–1.5486	0.1220	–	–
C(z5)6	–0.0715	0.0475	587	–1.5062	0.1325	–	–
C(z5)7	–0.0989	0.0472	586	–2.0956	0.0365	–	–
C(z5)8	–0.1036	0.0477	585	–2.1702	0.0304	–	–
C(z5)9	–0.1343	0.0472	583	–2.8451	0.0046	–	–
C(z5)10	–0.0837	0.0475	583	–1.7635	0.0783	–	–
C(z5)11	–0.0477	0.0484	584	–0.9859	0.3246	–	–
C(z5)12	0.0648	0.0483	584	1.3434	0.1797	–	–

Estimate – estimated coefficient, SE – Standard Error, df – degrees of freedom, t – t-statistic, Pr (> |t|) – p-value for t-test, F value – ANOVA F-statistic, Pr (>F) – p-value for F-test.

LMM analysis involves the random effects. The variance components and the derived intraclass correlation coefficient (ICC) are presented in Table 6. These values quantify the proportion of residual variance (unexplained by the fixed effects) that is attributable to group membership.

Table 6. Random effects variance vomponents and ICC

Tabela 6. Komponenty wariancji efektów losowych i ICC

Grouping level	Variance	ICC (proportion of total random variance)	Interpretation
z1 (Mine)	0.0296	33.2%	Between-mine variance
z2:z1 (Seam-within-Mine)	0.0031	3.5%	Between-seam (within-mine) variance
Residual (within-Seam) variance	0.0566	63.3%	Residual variance
Total random variance	0.0893	1.0000	

The ICC results indicate that 33.2% of the residual variance results from systematic differences between mines, and an additional 3.5% stems from differences between seams within those mines. This implies that mine-specific factors (e.g., organizational culture, infrastructure condition), which were not captured by the fixed effects, have a substantial impact on the achieved longwall advance. These estimated random effects are shown in Table 7.

The final linear mixed model predicting z27 for observation i within seam k of mine j can be expressed as:

$$z27_{ijk} = \underbrace{\left(\beta_0 + \beta_{z7} \cdot z7_{ijk} + \beta_{z8} \cdot z8_{ijk} \ldots + \beta_{z26} \cdot z26_{ijk} + f_M\left(M\right)\right)}_{\textit{Fixed Effects Part}} +$$

$$+ \underbrace{u_{0j}}_{\substack{\textit{Random Effect} \\ \textit{for Mine } j}} + \underbrace{u_{0jk}}_{\substack{\textit{Random Effect} \\ \textit{for Seam } k \\ \textit{within Mine } j}} + \underbrace{\int_{ijk}}_{\textit{Residual Error}}$$

↳ $z27_{ijk}$ – the predicted z27 for observation i in seam k of mine j,
β_0 – the fixed intercept, representing the baseline predicted z27,
$\beta_{z7}, \ldots, \beta_{z26}$ – the fixed-effect coefficients representing the estimated change in z27 for a one-unit increase in the respective continuous predictor variable,

Table 7. Estimated random effects (u_{kj}) for Mine (z1) and Seam-within-Mine (z2 : z1)

Tabela 7. Oszacowane efekty losowe (u_{kj}) dla Kopalni (z1) i Pokładu w Kopalni (z2 : z1)

Mine (j)	Mine 1	Mine 2	Mine 3
Mine Effect (u_{0j})	–0.0269	–0.1924	0.2193
Seam (k)			
S1	–	0.0292	–
S2	–	–	–0.0032
S3	0.0283	–	–
S4	–	–0.0047	–
S5	–	–0.0570	–
S6	–	–	0.0372
S7	–	–	–0.0110
S8	–	–0.0127	–
S9	–	–0.0346	–
S10	0.0015	–	–
S11	–0.0747	–	–
S12	–	0.0596	–
S13	0.0643	–	–
S14	–0.0139	–	–
S15	0.0117	–	–
S16	–0.0497	–	–
S17	0.0297	–	–

$f_m(M)$ – the fixed effect contribution of the month (C(z5)) for observation ijk. It represents the deviation for the specific month relative to the reference month (month 1),

u_{0j} – the random intercept for mine j, representing the deviation of the average z27 for mine j from the overall average predicted by the fixed effects,

u_{0jk} – the random intercept for seam k nested within mine j, representing the deviation of the average z27 for seam k within mine j from the average for mine j,

ε_{ijk} – the residual error for observation i, representing the random, unexplained variation.

3. Discussion

The developed longwall face advance model with LMM method allowed for a quantitative assessment of the impact of selected geological-mining and organizational factors on the z27 – Longwall advance per shift with production. The results clearly indicate that forecasting this key parameter is a complex problem in which operational and organizational factors play an equally, and at times even more dominant role than the inherent geological-mining conditions. This strong influence of organizational factors is evident in both the model's fixed effects and the random effects.

The analysis of the predictive power of the fixed effects (Table 4, Figure 11) demonstrated that the variable with the greatest impact on the model was z23 – Share of production shifts. This strong, positive relationship is substantively justified: a higher share of production shifts indicates better organization and higher technical availability, which translates not only to greater monthly advance but also to higher unit efficiency (advance per shift). The strong negative impact of z18 – Share of start-up or completion stage further confirms that unstable operational phases drastically reduce average performance. Geological-mining factors, such as z14 – Longwall panel width, z13 – Longitudinal inclination in advance direction, and z17 – Fault indicator, also showed a statistically significant negative impact, which aligns with engineering practice.

An interesting result is the identified positive influence of hazard variables: z20 – Spontaneous combustion tendency and z21 – Rockburst hazard level. This should not be interpreted as a "beneficial" effect of the hazard itself. A probable explanation is that operations in areas with elevated hazard levels are often prioritized, receiving better technical preparation, increased resource allocation, and more rigorous supervision (Burtan 2016; Ćwiek 2011). For example, high-hazard zones may receive dedicated crews, enhanced prophylactic measures, or more intensive maintenance schedules to prevent downtime, which paradoxically leads to higher operational efficiency and better advance. This finding is particularly notable given that the mining operations in the analyzed area are already conducted at significant depths under difficult conditions with high inherent hazards, where one might expect only negative impacts. It is also noteworthy that z15 – Mining depth, which showed a positive correlation in the Spearman analysis (Figure 7), was not selected as a predictor in the final model, likely because its effect was rendered non-significant after controlling for other factors.

These results partially align with previous research on mining difficulty (Sobczyk and Kopacz 2018; Sobczyk et al. 2024). Factors identified therein as significantly increasing costs (e.g., related to hazards) also show a significant impact on longwall advance in our model. However, this model goes a step further: instead of aggregating factors into a single difficulty index (e.g., AHP), it quantifies the direct, unit-level impact of each predictor on a physical measure of advance, which offers greater applicational value for planning engineers.

An important finding is the high contribution of random effects to explaining the variability in longwall advance. The Conditional R^2c (0.64) is significantly higher than the Marginal

R^2m (0.43), and the ICC analysis (Table 6) revealed that membership in a specific z1 – Mine alone accounts for 33.2% of the residual variance. This implies that immeasurable, mine-specific factors – such as organizational culture, internal procedures, technical infrastructure condition, or management competencies – have an impact on longwall advance that is just as strong as the measured geological or technical parameters. The negligible influence of z2 – Seam (3.5% ICC) suggests that most of the geological variability between seams was successfully captured by the fixed effects predictors.

The identification of statistically significant seasonality (Table 5), with decreased advance in the summer and early autumn months (July–September, corresponding to C(z5)7–C(z5)9), is likely related to work organization during holiday periods, leading to less stable crew staffing and potential disruptions.

The practical implications of the presented model are twofold. First, it can serve as a tool for the realistic calibration of mining production schedules. Instead of adopting fixed, "expert" norms for longwall advance rates, a schedule could dynamically recalculate expected advance based on querying the deposit model for difficulty data related to each segment. Second, the model can be used as a basis for creating bonus systems based on objective indicators, accounting for the degree of difficulty (hardship) of the conditions in which a given mining team operates.

However, limitations of the study must be noted. The relatively high number of predictors in the final model in relation to the number of observations raises the risk of overfitting, where the model might capture dataset-specific variance rather than general relationships. Although the model was validated based on AIC and residual analysis. The lack of external validation (cross-validation or testing on an independent dataset) means that the generalization of the specific coefficients should be treated with caution. A limitation also arises from the aggregation of data into monthly intervals, which are analytically stable; it averages out many short-term phenomena critical to longwall advance (e.g., breakdowns, technological stoppages). Access to reliable shift-level (or daily) geological data would allow for the construction of models with much higher resolution, better forecasting operational fluctuations, and crucially, revealing the deeper causal mechanisms behind these operational dynamics.

Furthermore, the numerical treatment of some ordinal variables (like natural hazards categories) represents a methodological trade-off. While this approach aligns with previous research on mining difficulty's impact on production and costs and facilitates the straightforward application of the analytical formula in planning tools, it also carries inherent limitations regarding the assumption of linearity. Optimally, such an analysis would be based on the underlying continuous measurement data from which these hazard categories are derived (e.g., measured gas levels, seismic readings, stress data), though such data were not available in the analyzed deposit models. Access to this more granular data would allow the model to move further beyond a correlational "black-box" (which, for instance, reported the counter-intuitive positive effect of hazards) and toward a clearer understanding of how specific conditions and the operational responses to them truly influence longwall advance.

Conclusions

The aim of this article was to develop a longwall face advance model suitable for use in production planning systems, which accounts for local geological conditions, natural hazards, and technical and organizational parameters. This goal was achieved by building and validating a Linear Mixed Model (LMM) using integrated spatial and operational data from three hard coal mines. The resulting model, which explains nearly 64% of the total variance of longwall advance (conditional $R^2c = 0.64$), serves as a key component of the integrated production planning methodology.

The main conclusions from the research are as follows:

1. The application of the LMM methodology is an adequate approach for analyzing mining advance, as it correctly incorporates the hierarchical data structure (mine, seam) and allows for the quantitative separation of the influence of fixed (measurable) factors from random (immeasurable, group-specific) factors.
2. Organizational factors (specifically the share of production shifts) and operational ones (the share of start-up or completion stages) exhibit a dominant impact on the longwall advance per shift, often stronger than many geological factors.
3. Key geological and mining factors (such as longwall panel width, fault index, and longitudinal inclination) have, as expected, a statistically significant negative impact on longwall advance.
4. The random effects analysis revealed that the majority of the unexplained variance (33.2%) results from systematic, immeasurable differences between mines, rather than between seams (3.5%), indicating the fundamental role of mine-level management, organizational, and technical factors.

Modelling longwall advance inherently involves a significant stochastic component. Within this context, the research demonstrates a distinctive scientific contribution and a high utilitarian value of the proposed statistical model, which can be effectively integrated into decision-support tools for mine production planning, thereby enhancing the efficiency of mineral deposit management.

Future research, pending the availability of relevant data, should focus on applying the proposed modelling methodology to more granular datasets. Such an approach would facilitate the identification of short-term disturbances (e.g., equipment failures) and support the development of more precise models, thereby strengthening the foundation for effective operational planning.

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The Authors have no conflict of interest to declare.

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OPTIMIZING RESOURCE MANAGEMENT UNDER VARIABLE GEOLOGICAL AND MINING CONDITIONS USING A LONGWALL ADVANCE MODEL

K e y w o r d s

underground mining, production planning, resource management,
linear mixed models (LMM), geological modelling

A b s t r a c t

Production planning in underground hard coal mines faces high uncertainty from geological variability. The longwall face advance is a key parameter determining production outcomes. This article models this advance rate based on local geological, hazard, technical, and organizational parameters. Instead of tonnage (a composite parameter), this research models the linear advance rate itself, representing the primary and most unpredictable component of excavation. This provides a utilitarian tool for decision-support systems and efficient deposit management.

The research used integrated 5-year data from three hard coal mines, acquired from digital deposit models, scheduling systems, and operational reports, and aggregated monthly. Following a selection from 71 variables, a final set of 26 independent variables and one dependent variable (longwall advance per shift with production) was chosen. Linear Mixed Models (LMMs) were applied to incorporate the hierarchical data structure (seams nested within mines).

The model demonstrates a good fit, explaining 64% of total variance (conditional $R^2c = 0.64$), while fixed effects alone account for 43% (marginal $R^2m = 0.43$). Results indicate organizational factors have a dominant impact. The random effects analysis revealed 33.2% of residual variance stems from immeasurable, systematic differences between mines, highlighting the crucial role of mine-specific management factors. By successfully quantifying these diverse factors within a stable LMM, this study provides a model with improved predictive accuracy, establishing an effective foundation for operational planning and resource management.

OPTYMALIZACJA PROCESU ZARZĄDZANIA ZASOBAMI W ZMIENNYCH WARUNKACH GEOLOGICZNO-GÓRNICZYCH Z WYKORZYSTANIEM MODELU POSTĘPU ŚCIANY WYDOBYWCZEJ

S ł o w a k l u c z o w e

górnictwo podziemne, planowanie produkcji, zarządzanie zasobami,
liniowe modele mieszane (LMM), modelowanie geologiczne

S t r e s z c z e n i e

Planowanie produkcji w kopalniach węgla kamiennego obarczone jest dużą niepewnością wynikającą ze zmienności geologiczno-górniczej. Postęp ściany jest kluczowym parametrem determinującym wyniki produkcyjne. W artykule modelowano tempo postępu ściany w funkcji lokalnych uwarunkowań geologicznych, zagrożeń oraz parametrów technicznych i organizacyjnych.

Badania koncentrują się na modelowaniu postępu liniowego (podstawowego i najbardziej nieprzewidywalnego komponentu eksploatacji) zamiast tonażu (parametru złożonego). Dostarcza to narzędzia dla systemów wspomagania decyzji i efektywnej gospodarki złożem.

Badania oparto na zintegrowanych, 5-letnich danych z trzech kopalń węgla kamiennego. Dane pozyskano z cyfrowych modeli złóż, systemów harmonogramowania i raportów operacyjnych, agregując je miesięcznie. Po selekcji z 71 zmiennych wybrano 26 predyktorów i 1 zmienną zależną (postęp ściany na zmianę produkcyjną). Zastosowano Liniowe Modele Mieszane (LMM) w celu uwzględnienia hierarchicznej struktury danych (pokłady w kopalniach).

Opracowany model wykazuje dobre dopasowanie, wyjaśniając 64% całkowitej wariancji (warunkowe $R^2c = 0.64$), przy czym efekty stałe odpowiadają za 43% (marginalne $R^2m = 0.43$). Wyniki wskazują na dominujący wpływ czynników organizacyjnych. Analiza efektów losowych ujawniła, że 33.2% wariancji resztowej wynika z niemierzalnych, systematycznych różnic między kopalniami, co podkreśla kluczową rolę czynników zarządczych. Rezultatem niniejszej pracy jest stabilny model LMM, który poprzez integrację i kwantyfikację czynników geologicznych, operacyjnych oraz organizacyjnych (włącznie z efektami losowymi) oferuje zwiększoną zdolność prognostyczną. Model ten tworzy tym samym efektywną podstawę dla planowania operacyjnego i gospodarki zasobami.