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## **Optimization of support parameters for reusable** mining excavations based on a neuro-heuristic prognostic model

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### Abstract:

This publication delves into geomechanical processes encountered during sequential longwall mining of coal seams, with a unique focus on reusing the conveyor track of the prior longwall as the ventilation pathway for the subsequent longwall. An in-depth geomechanical rationale is provided for the reuse of excavations within jointed rock formations. To ascertain the critical roles played by various support and protective elements at each distinct mining stage, a comprehensive analysis is performed using finite element techniques to delineate the three-dimensional stress-strain characteristics of the rock mass. Employing an innovative methodology integrating multifactorial analysis, contemporary structural identification algorithms, and a neuroheuristic approach for predictive mathematical modeling, an integral stability metric for reusable mining excavations is introduced. Specifically, this metric quantifies the relative preservation of the excavation's cross-sectional area following its connection to the second longwall. Furthermore, the study tackles the challenge of nonlinear optimization through the application of the generalized reduced gradient method (Frank-Wolfe), ultimately deriving the optimal combination of factors that maximizes the preservation of the crosssectional area for these reusable excavations.

Keywords: longwall mining, coal seam, geomechanical processes, excavation reuse, jointed rocks, Finite Element Analysis, stress-strain analysis, support parameters, multifactorial analysis, nonlinear optimization



### 1. Introduction

Within the mining industry, a fundamental component of operational costs revolves around the establishment and upkeep of critical technological excavations (gateroads), including conveyor tracks (maingate), ventilation pathways (tailgate) etc. In recent years, Ukrainian mining operations have embarked on a path of modernization, driven by the imperative of achieving economically sustainable extraction levels. This transformation has entailed the overhaul of coal reserve preparation methodologies, with a significant shift towards adopting integrated longwall mining systems featuring backfilling techniques and the reutilization of essential technological excavations [1-3].

The proactive recreation of coal preparation infrastructure, both for active longwall mining operations and the provisioning of pre-prepared coal reserves, necessitates an unwavering commitment to reliability throughout all facets of mining technology. This commitment serves as the linchpin for ensuring seamless progress, curtailing downtime associated with equipment reconfiguration in novel mining zones, and substantially mitigating the risks linked to the maintenance of these vital excavations. The attainment of these objectives fundamentally hinges on the sustained operational integrity of reusable excavations [4-6].

Extensive research endeavors spanning multiple years, focused on evaluating the condition of preparatory excavations in mines within Western Donbas, have unveiled the intricate challenges inherent in supporting these excavations, particularly in areas influenced by neighboring longwall operations. These complexities are further compounded within the context of geologically weak and jointed rock formations. Numerous experimental investigations illustrate the increasing displacements within the gateroad when its cross-section intersects with the zone influenced by a longwall [7-10].

Based on accumulated experience in various conditions within Ukrainian mines and drawing from global expertise, different measures are employed to enhance the stability of excavations in areas influenced by coal extracting. However, integrating these individual measures into a comprehensive approach that is universally applicable to mines within a specific region necessitates a foundation rooted in the mechanics of coal-rock masses.

The parameters of support and protective systems are designed to be adjustable according to the magnitude and nature of the rock pressure manifestations, forecasted through a combination of accumulated experience, synthesis of empirical observations, and mathematical modeling of geomechanical processes.

Numerous studies have been dedicated to exploring geomechanical processes in the rock mass within the influence a longwall face [10-14]. However, insufficient attention has been devoted to the quantitative assessment of the impact of various stability assurance elements concerning the connection between technological excavations and longwall, particularly from the perspective of refining the technology of reinforcement and protection of technological excavations for the reuse purpose of their reuse [15].

### 2. Materials and Methods

### 2.1. Numerical three-dimensional modeling

We analyze the geomechanical processes within the rock mass at each stage, harnessing the advantages of numerical methods to determine the stress-strain state of the rock mass. In order to discern the role of various support and protection elements for excavations, we have considered a 3D model of the rock mass with a minimal number of layers: a coal seam with a thickness of 2.0 m and sandstone as a roof and floor of the gateroad.

The depth of the excavation is 400 meters, and the specific weight of the rock is assumed to be 25 kN/m<sup>3</sup>. Consequently, the vertical stresses in the intact rock mass amount to 10 MPa. The rock mass is considered as an elastic-plastic medium, with deformations following the Hoek-Brown strength theory. The modeling is carried out using RS3 software (Rocscience), which implements the finite element method in a three-dimensional setting. The model had dimensions of  $200 \times 50 \times 50$  m and was



divided into tetrahedron elements. The finite element analysis was conducted incrementally, ensuring that the deformations of rocks at a given stage were considered in the subsequent stage [16].

The computational framework for the three-dimensional modeling and the finite element mesh of the model are illustrated in Fig. 1.



**Fig. 1.** Computational Scheme for Incremental Determination of Stress-Strain Components in the 'Longwall – gateroad - Longwall: a) Model Structure, b) Finite Element Mesh and restrains of the Model

In Fig. 2, the stages of three-dimensional modeling are depicted, simulating the creation of a gateroad and the gradual formation of the excavated space for two longwalls, as well as the development of rock displacements while considering various combinations of reinforcement and support.

At Stage 1, the gateroad in the intact mass is modeled, and support system is installed (Fig. 2a). At Stage 2, a void representing the first longwall is introduced by modifying boundary conditions (Fig. 2b). In Stage 3 (Fig. 2c), a void representing the second longwall is added. At this stage, the excavated space of the first longwall is replaced with material simulating the disintegrated rock mass after the overlying rock has collapsed. The characteristics of the stress-strain state of the rock mass are evaluated at each modeling step.

The initial data for the simulation are as follows: the mining depth; the gateroad dimensions; the coal seam thickness; the strength and deformation properties of the rock mass and coal seam; data on the rock jointness; parameters of the steel lining and the data on the rockbolt location. The parameters of a packwall made of wood or mineral binders to create a strong support pillar between the gateroad and mined-out space (a gob) should be also taken in consideration.







The multi-variant three-dimensional modeling has enabled the identification of general trends in the development of rock displacements in the surrounding zone of connection between the excavation and the longwall. This forms the basis for constructing a predictive model.

# 2.2. The development of a multifactorial mathematical model for the stability of the reusable excavation

The execution of extensive numerical experiments allows for the generalization of deformation trends within the rock mass at various stages of longwall mining with the reuse of gateroads. Utilizing



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the methodology developed in [17], which is based on modern structural identification algorithms and an inductive approach for creating predictive mathematical models, we introduce an integral indicator for ensuring the stability of the gateroad influenced by the excavated spaces of two longwalls.

As a suitable integral feature, it is prudent to select the relative value of the cross-sectional area of the gateroad that will be preserved after its connection with the second longwall.

In general, the problem of mathematical modeling can be formulated as follows: there are observational data or results from numerical experiments, and the objective is to construct a model to describe them. Subsequently, two possible scenarios may arise:

- When the model's structure is known (e.g., linear, quadratic, exponential, etc.), the task is solely to identify the model's parameters. This falls within the domain of parametric optimization.
- If the model's structure is unknown, the goal is to discover the optimal model and identify its parameters, which are optimal according to a predictive criterion. This constitutes the problem of structural optimization (identification).

In this research, we focus on generating a multifactorial mathematical model for the stability analysis of preparatory operations, using a structural identification approach.

Group Method of Data Handling (GMDH) is a machine learning and data analysis technique used for regression and classification tasks. GMDH is an algorithmic approach that belongs to the family of machine learning methods known as self-organizing data analysis techniques [18].

The key idea behind GMDH is to develop a model that can capture complex relationships between input variables (features) and output variables (target) by creating a series of polynomial equations. These equations are generated through a process of group modeling and optimization. GMDH builds a series of models, each more complex than the previous one, and selects the best model based on certain criteria, often aiming for the best trade-off between model accuracy and complexity.

The complexity of the model structure is assessed based on the number of polynomial terms. The iterative search procedure involves calculating the criterion while gradually increasing the complexity of the model structure. When selecting the model structure, we are guided by two principles: to strive for the model to be as simple as possible (the principle of parsimony) and to improve the model by assessing its adequacy and predictive properties (the principle of adequacy).

A distinctive GMDH feature is the organization of the search for the optimal model structure using both internal and external selection criteria. A criterion is termed internal if it is calculated over the entire data sample. An external criterion is calculated using new information that was not used to estimate the model coefficients [19]. Therefore, to ensure the model's quality predictive properties, i.e., its stability concerning new data, it is necessary to divide the entire dataset into two parts. The first dataset is used for model construction and is referred to as the training data. The second dataset serves as new data and is used to assess the quality of the constructed model. This dataset is known as the validation data.

The methodology applied in these studies is as follows:

- Determine a class of models with increasing complexity.
- Divide the data (Experimental Data = Training Data + Validation Data).
- For a given level of complexity, estimate the model parameters using the first dataset (training data) and apply an internal criterion.
- Validate the model using the second dataset with the application of an external criterion.
- If the external criterion reaches a minimum, the best model has been found; otherwise, it is necessary to increase the model's complexity and return to step 3.

In terms of their structure, GMDH algorithms are closely related to self-learning algorithms for multilayer pattern recognition systems or neural networks [20]. The significant difference lies in the fact that polynomial GMDH algorithms operate with continuous variables. Only continuous variables allow for finding the minimum of an external criterion, which determines the optimal structure of the mathematical model.



### 2.3. The formulation of a problem for conditional optimization

To determine the most rational combination of factors in order to preserve the maximum crosssection of reusable gateroad, we will solve a problem of constrained optimization of a multivariable function obtained using the GMDH algorithm.

The method of reduced gradient can be considered as a nonlinear extension of the simplex method, which selects a basis, determines the search direction, and performs linear search in any large iterative system of nonlinear equations at each step.

The Generalized Reduced Gradient Method (Frank-Wolfe) uses second-order derivative approximations to accelerate the process and verify whether the optimal solution has been found. It is an advancement of the reduced gradient method and can be applied to solve problems with nonlinear constraints [21, 22].

Let's consider the algorithm of the Generalized Reduced Gradient Method for solving the problem:

$$nax F = f(x_1, x_2, \dots, x_n) \tag{1}$$

under the following restrictions:

$$\sum_{j=1}^{n} a_{ij} x_j \le b_i , \ (i = \overline{1, m})$$
<sup>(2)</sup>

$$x_j \ge 0, \ (j = 1, n)$$
 (3)

A characteristic feature of problems solvable using this method is that their system of constraints should only contain linear inequalities. This feature forms the basis for replacing the nonlinear objective function with a linear one in the vicinity of the examined point. As a result, solving the original problem is reduced to sequentially solving linear programming problems [23, 24].

Algorithm of the method is as follows. Determine a point belonging to the feasible region. Let this point be denoted as  $X^{(k)}$ . Then, compute the gradient of the function at this point

$$\nabla f(X^{(k)}) = \left[\frac{\partial f(X^{(k)})}{\partial x_1}, \frac{\partial f(X^{(k)})}{\partial x_2}, \dots, \frac{\partial f(X^{(k)})}{\partial x_n}\right]$$

and form a linear function:

$$F = \frac{\partial f(X^{(k)})}{\partial x_1} x_1 + \frac{\partial f(X^{(k)})}{\partial x_2} x_2 + \dots + \frac{\partial f(X^{(k)})}{\partial x_n} x_n$$
(4)

We proceed to a new problem, which involves maximizing the function (4) subject to constraints (2) and (3). Let the solution to this problem be determined by the point  $Z^{(k)}$ . Then, the coordinates of point  $X^{(k+1)}$  are taken as the new feasible solution for the original problem (1) - (3).

$$X^{(k+1)} = X^{(k)} + \lambda_k (Z^{(k)} - X^{(k)}),$$
(5)

where  $\lambda_k$  is a certain number called the computation step, and its value should be between zero and one, meaning  $0 \le \lambda_k \le 1$ . This step  $\lambda_k$  is usually chosen arbitrarily or determined in such a way that the value of the function at point  $X^{(k+1)}(f(X^{(k+1)}))$ , which depends on  $\lambda_k$ , is maximized. To do this, it is necessary to find the solution to the equation:

$$\partial f(X^{(k+1)})/\partial \lambda_k = 0$$

and select its maximum root. If the value obtained in this way turns out to be greater than one, then set  $\lambda_k = 1$ .

After determining  $\lambda_k$ , you find the coordinates of the point  $X^{(k+1)}$ , calculate the value of the objective function at that point, and, using the inequality:

$$\left| f(X^{(k+1)} - f(X^{(k)}) \right| < \varepsilon \tag{6}$$



(where  $\varepsilon$  is a sufficiently small number), it is determined whether it is necessary to transition to a new point  $X^{(k+2)}$ . If such a necessity exists (the inequality is not satisfied), then the gradient of the objective function is calculated at the point  $X^{(k+1)}$ .

Then we proceed to the corresponding linear programming problem, find its solution, determine the coordinates of point  $X^{(k+2)}$ , and investigate the necessity of further computations. It should be noted that after performing a finite number of such steps, a solution to the original nonlinear programming problem (1)-(3) is obtained with the required accuracy.

This algorithm has been applied to find the optimal support parameters for the predictive function of preserving the reusable excavation cross-section.

### 3. Results

### 3.1. Results of numerical modeling of the stress-strain state of the rock mass

A multifactor computational experiment was conducted. Under other equal conditions, the following parameters were varied: "relative width of the protective element" (w/m) within a range from 0.6 to 0.8; the stiffness of the protective element ( $k_n$ ) with a range of variation from 0 to 10<sup>4</sup> MPa/m.

The creation of a stable rock lining is not possible without the implementation of a rational roof bolting scheme [25]. To quantitatively consider the parameters of roof bolting, we introduce the generalized factor "relative number of bolts per cross-sectional area of the excavation" (Na), which varies from 0 (without roof bolting) to 0.6 (11 bolts, relative to a cross-sectional area of 17.7 m<sup>2</sup>). Another factor characterizing the support system is "spacing of the installation of the metal arch support" (q) with a range of variation from 0.5 to 1 m.

The fifth integral factor introduced into the analysis is the parameter of mining conditions according to Yu. Zaslavsky [26], which is the ratio of the initial stress field  $\gamma$ H to the uniaxial compression strength of rocks. This factor varies within the range of 0.3 - 0.7 in terms of Western Donbas coal mines. For a full factorial analysis, it is necessary to perform 3<sup>5</sup> experiments, i.e., the calculation of 243 finite element models was conducted.

The result of the modeling is the maximum displacements in the roof and floor of the excavation, as well as the total preservation of the gateroad cross-section.

For each combination of the varied factors provided by the computational experiment plan, modeling was carried out by organizing three stages, each of which corresponds to a specific stage of the mutual arrangement of the excavation and two longwalls.

The displacement of the excavation contour for one of the 243 numerical models is shown in Fig. 3.







**Fig. 3.** Development of displacements during longwall mining: a) excavation of a gateroad in the intact mass; b) formation of the excavated space of the first longwall; c) formation of the excavated space of the second longwall and filling the excavated space of the first longwall with disintegrated material

The purpose of the computational experiment is to establish the dependence of the initial data - maximum displacements in the roof and floor of the excavation and total preservation of the cross-section - on the varied factors.

### **3.2.** Creation of a predictive model and optimization of support parameters.

The execution of extensive numerical experiments allowed us to generalize the trends in the development of rock mass displacements at various stages of longwall mining with the gateroad reuse.

The fragments of initial data for the GMDH analysis and the corresponding values of the percentage of the gateroad cross-section that will be preserved (based on multi-variant modeling results) after merging with the second longwall are presented in Table 1.

	γH/Rc	K <sub>n</sub> , MPa/m	Na	w/m	q, m	preserved cross-section (S), %
N⁰	0.3-0.7	0-10000	0-0.6	0.6-0.8	0.5-1	
1	0.3	0	0.00	0.6	1	12
2	0.7	0	0.00	0.6	1	10
3	0.3	10000	0.00	0.6	1	17
4	0.3	0	0.51	0.6	1	14

Table 1. Data for GMDH analysis of the gateroad stability



5	0.3	0	0.00	0.8	1	15
6	0.3	0	0.00	0.6	0.5	16
7	0.3	10000	0.51	0.6	1	27
8	0.3	10000	0.00	0.8	0.5	25
9	0.3	10000	0.51	0.8	0.5	70
10	0.7	10000	0.51	0.8	0.5	60
11	0.3	5000	0.51	0.8	0.5	68
12	0.3	10000	0.28	0.8	0.5	55
13	0.5	5000	0.28	0.7	0.75	50
14	0.3	3000	0.28	0.8	0.5	62
15	0.7	5000	0.17	0.6	0.5	50
16	0.5	5000	0.40	0.8	1	48
17	0.7	8000	0.17	0.7	0.5	52
18	0.3	10000	0.40	0.6	0.75	53
19	0.6	10000	0.40	0.6	0.75	43
20	0.3	5000	0.17	0.6	0.5	41
21	0.4	5000	0.28	0.7	0.75	50
22	0.6	2500	0.17	0.7	1	29
23	0.4	8000	0.45	0.8	0.6	65
24	0.7	10000	0.51	0.7	0.5	52
25	0.8	10000	0.51	0.8	0.5	55

The data from Table 1 were processed using combinatorial and iterative algorithms of Group Method of Data Handling. The dependency generated by the iterative algorithm was selected as the most adequate predictive model based on the minimum external criterion.

$$S = \frac{w}{m} \cdot \left(218N_a - 14\frac{\gamma H}{R_c}\right) + 0.017k_n^{2/3} - 186N_a^2 - 9,9q^2 + 25$$
(7)

The coefficient of determination is 0.94 for the training subset and 0.92 for the validation subset. The average value for the entire investigated data set is  $R^2=0.93$ .

The graphical adequacy of the predictive model (7) is visualized in Figure 4. The input values for the GMDH analysis are shown in gray, the values of the function (7) obtained for the training subset of data are shown in blue, and the results of the forecast and the confidence interval are shown in red.



**Fig. 4.** Visualization of the predictive model for preserving the cross-sectional area of the reusable excavation



Publisher: KOMAG Institute of Mining Technology, Poland © 2023 Author(s). This is an open access article licensed under the Creative Commons BY-NC 4.0 (<u>https://creativecommons.org/licenses/by-nc/4.0/</u>) The influence of each factor, weighted by coefficients, on the resulting indicator is as follows: "relative number of bolts per cross-sectional area of the excavation" ( $N_a$ ) - 32%, "relative width of the protective element" (w/m) - 28%, 'spacing of the installation of the metal arch support' (q) - 18%, development parameter ( $\gamma H/\sigma$ ) - 13%, and the stiffness of the protective element ( $k_n$ ) - 9%.

To determine the most rational combination of factors for the purpose of preserving the maximum cross-sectional area of the reusable excavation, we will solve a multi-variable conditional optimization problem.

Using the generalized reduced gradient method, we have solved the problem (1)-(3) for the predictive function (7). As a result of the optimization, it was determined that the maximum of the function (7) under the specified constraints of input variables is

 $S_{max}(N_a, w/m, q, kn, \gamma H/Rc) = 67.9\%$ 

So, with the best combination of input variables, it is forecasted that up to 68% of the cross-sectional area of the reusable excavation, influenced by two longwalls will be preserved. The maximum is achieved with the following variable values:  $N_a = 0.47$ ; w/m = 0.8; q = 0.5;  $k_n = 10\ 000\ MPa/m$ ,  $\gamma H/\sigma = 0.3$ . It should be noted that these values of the factors (Na, w/m, q, k<sub>n</sub>) are optimal for all values of the parameter of mining condition within its range of variation (from 0.3 to 0.7).

Therefore, it should be noted that the prospects of reusing excavations are largely determined by a complex of geomechanical and technological parameters during the final sections of the longwall mining, ensuring the stability of the gateroad. Further maintenance does not pose significant difficulties, taking into account the implementation of appropriate repair and restoration measures. However, the scope of these measures is significantly reduced with adequate forecasting of rock pressure and the design of an appropriate support and protection system for the excavation.

### 4. Conclusions

- 1. Multivariate modeling of the "longwall reusable gateroad longwall" system has demonstrated that sequential installing various support elements into the model, such as metal arch supports, steel-polymer bolts, and cable bolts, the role of each of them in ensuring excavation stability has been highlighted and has served as the basis for generalized analysis using the Group Method of Data Handling (GMDH). Thus, the role, feasibility, and sequence of measures to ensure the stability of gateroads, sufficient for their reuse, have been substantiated.
- 2. Using the Group Method of Data Handling (GMDH) based on modern structural identification algorithms and an inductive approach to create predictive mathematical models, a relationship has been obtained for the residual cross-sectional area of the excavation, which serves as an integral indicator of the stability of preparatory excavations influenced by two longwalls. This relationship is dependent on mining-geological and mining-technical parameters, the significance of which has been justified in the research. These parameters include the relative width of the protective element (w/m), the contact stiffness coefficient in the protective element (k<sub>n</sub>), the number of roof bolts per cross-sectional area of the excavation (N<sub>a</sub>), the spacing of the installation of the metal arch support (q), and the parameter of development conditions ( $\gamma$ H/ $\sigma$ ). It has been determined that the influence of each factor on the resulting indicator is as follows: N<sub>a</sub> 32%, w/m 28%, q 18%, k<sub>n</sub> 9%, and  $\gamma$ H/ $\sigma$  13%.
- 3. Using the Generalized Reduced Gradient Method (Frank-Wolfe), the problem of nonlinear optimization for the obtained multifactor function the residual cross-sectional area of the excavation (7) has been solved, and optimal parameters have been determined. These parameters maximize the function, ensuring the preservation of the maximum cross-sectional area of the reusable excavation influenced by two longwalls.



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