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Real-time forecasting of key coking coal quality parameters using neural networks and artificial intelligence

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Artur Dyczko
Mineral and Energy Economy Research Institute, Polish Academy of Sciences, J. Wybickiego str. 7A, Krakow, PL-31261, Poland, http://orcid.org/0000-0001-6387-5339

Abstract

High quality coke is a key raw material for the metallurgical industry. The characteristics of the coal have a significant influence on the parameters of the coke produced and, consequently, on the valuation of coal deposits and the economic assessment of mining projects. Predicting the quality of coking coal allows for the optimisation of production processes, including the planning and management of operations and the early detection of quality problems. In this study, using the principles of a smart mine, it is proposed to determine the quality of coal based on the combination of mining and geological conditions of mineral deposits and its quality indicators. Possible interrelationships between the quality of the coal in the deposit and the characteristics of the final product have been identified. A neural network is used to determine the priority of individual indicators that have a significant impact on the quality of coking coal. An important part of the research is its practical implementation in the conditions of the Jastrzębska Spółka Węglowa SA. Qualitative and quantitative parameters of coking coals were obtained for each mine of the region by the method of sampling and statistical processing of data such as: degree of metamorphism, thickness, deviation of volatile substances, presence of phosphorus, ash content, etc. For their evaluation, the Group Method of Data Handling was used to compare the factors of quality indicators depending on the priority of influence on the final characteristics of the coking coal. Based on the results obtained, it is shown that not all coal quality indicators have a significant impact on the quality of the final product. The study shows that it is possible to predict the main indicators (CRI – Coke Reactivity Index, CSR – Coke Strength after Reaction) of coke quality using neural networks based on a larger number of coal quality parameters and to eliminate parameters that have virtually no influence on the value of the final product. This method can also be used to improve the results of economic valuation of a deposit and to better plan exploration and mining operations.

Keywords:
coking coal; coal quality; neural network; artificial intelligence; Group Method of Data Handling (GMDH)

1. Introduction

Today, information and technology play a key role in all sectors of society and the economy in what is known as the Information Age or Digital Age. Technology 4.0 offers significant changes and opportunities across industries, including manufacturing, transport, energy, and others (**Fuchs, 2016**). The rapid development of computer technologies, the internet, mobile communications, artificial intelligence, and other digital innovations are creating new relationships in society and the industrial sector (**Pathak, 2022; Briševac and Kujundžić, 2016; Madandoust et al., 2012**). While they promise to increase productivity, efficiency, and innovation, they also pose challenges related to data privacy, cybersecurity, and workforce adaptation. Embracing and leveraging these technologies can lead to transformative benefits and competitive advantages in the digital age (**Polyanska, 2022**). However, it also opens many opportunities for innovation, development, and improvement, including mining, medicine, energy, and others (**Smith and Quiros, 2012**). Unfortunately, despite minor developments in AI, these processes have not yet significantly affected mining (**Dyczko, 2023a**).

Smart Mining and Grid Mining are two related concepts that focus on improving the efficiency, sustainability, and environmental impact of mining operations. Smart mining refers to the use of advanced technologies, such as artificial intelligence, Internet of Things (IoT) and automation, to improve the productivity, safety, and sustainability of mining processes. It involves the integration of various digital systems and data-driven technologies to optimize operations and decision-making (**Dychkovskyi et al., 2019**). The main aspects of smart mining mean the implementation of various automation and robotics on the surface and underground, monitoring and control, analytics and predictive modelling, correction of mining processes of big data operating other min-

Corresponding author: Artur Dyczko
e-mail address: arturdyczko@gmail.com

ing and near-mining activities (**Sharma and Maity, 2018; Sdvyzhkova et al., 2022**). This improves efficiency, reduces labour requirements, and enhances safety, proactive maintenance, early detection of problems and improves all operational mining issues (**Downes 2020**). The ability to provide real-time monitoring using sensors, cameras, and IoT devices is crucial. Equally important are the issues related to the acquisition, processing and analysis of large spatial data sets in the mining industry (**Krawczyk, 2023**). In addition, global trends towards circular economy concepts require a reassessment of traditional mining approaches to ensure long-term economic and environmental stability (**Markevych et al., 2022**). The use of advanced geological modelling and mine design, together with decision support methods, can optimise mine planning not only in terms of economic performance but also in terms of social and environmental impact (**Sobczyk et al., 2022**).

"Grid mining" is not a well-known concept in the context of mining. It may be a term specific to a certain domain or not widely recognized (**Sánchez et al., 2009**). However, it's important to consider that successful implementation of neural networks in mining requires the appropriate data collection, preprocessing, model training, and domain expertise. Mining companies need to invest in robust data infrastructure, skilled personnel, and integration strategies to fully leverage the benefits of neural networks in their operations.

Mining companies are using advanced technologies like machine learning and data analytics to enhance and streamline multiple facets of their operations. These technologies offer valuable tools for optimizing key processes such as exploration, mineral extraction, resource estimation, and equipment maintenance. By harnessing the power of machine learning and data analytics, mining companies can gain insight, improve efficiency, reduce costs, and make informed decisions throughout the entire mining lifecycle. From identifying potential mining sites to accurately estimating resources and implementing proactive maintenance strategies, these technologies play a pivotal role in driving productivity and sustainability in the mining industry (**Jinqiang et al., 2021; Chimunhu et al., 2022**).

Overall, the integration of machine learning and data analytics via neural networks in mining processes empowers companies to make data-driven decisions, optimize resource utilization, increase productivity, and reduce operational costs (**Kiani et al., 2021**). It enables them to navigate complex geological challenges, mitigate risks, and operate in a more sustainable and responsible manner (**Shavarskyi et al., 2022**). As technology continues to advance, mining companies are poised to further benefit from these transformative technologies, unlocking new opportunities and enhancing their competitive edge in the industry (**Małkowski and Juszyński, 2021; Lawal and Kwon, 2020**).

The author of this article is trying to change this situation. In his previous publication, he presented geological modelling of deposits, production design and planning of mining works using AI systems (**Dyczko, 2023b)**. Another interesting example was the approach to the presentation of mining models, which provides for the formation of a mine as a whole simulation system, in which all processes are output to the control centre. The mine was represented as one whole mechanism divided into separate elements, respectively, the simulation of each production process takes place with a certain margin of error. Moreover, infrastructure objects were presented only as a visual reproduction (**Dychkovskyi et al., 2009**). The processes taking place in mining operations were reproduced with the help of kinematic, statistical, and dynamic similarity (**Chen, et al., 1995**). Statistical similarity examines the consistency of statistical properties, kinematic similarity focuses on comparable motion patterns, and dynamic similarity ensures that the relevant physical forces and dynamics are preserved. Optimizing variable data in artificial neural networks for forecasting raw material prices for energy production is a critical step in improving the accuracy and reliability of the predictions (**Matyjaszek et al., 2020**). These concepts are crucial for scaling laws, modelling, and understanding complex systems across different scales or conditions (**Westbrook, 1981; Norouzi-Masir et al., 2021**). Mining operations involve several economic parameters that play a crucial role in determining the profitability and viability of a mining project. Profitability measures the financial returns and profitability of a mining operation and is a key indicator of its economic success (**Dychkovskyi et al., 2013; Gul, 2022**). The formation of simulation systems using AI technologies for underground and open pit mining and in various mining countries shows the correctness of the research direction chosen by the author of the article (**Gomilanovic et al., 2023; Šapina, M 2016; Fiket et al., 2023**). The focus of this work is to ensure the conformity of all types of similarities on which this work is focused when determining the quality characteristics of coal in operating mines.

By incorporating multiple perspectives into neural networks, mining operations can benefit from a more holistic understanding of their systems, improved decision-making capabilities, and increased operational efficiency. It allows the neural networks to use a wider range of data sources and extract meaningful insight from different perspectives, ultimately leading to more accurate predictions, better process control, and improved safety in mining operations. By taking into account statistical aspects, such as geological data, equipment status, and operational variables of the Jastrzębska Spółka Węglowa SA, I am trying to use neural networks to optimize these processes in a more comprehensive manner, leading to increased efficiency and productivity.

The analysis carried out shows that there is a necessity to improve the existing methods for determining the

parameters of quality coal. It is hypothesized that the CRI and CSR coal characteristics are related and can be determined by some geological parameters because coal itself is a carbon biomass that has undergone geological processes along with other mineral and organic carbon deposits.

2. Research methodology

The main researches were provided in the "Borynia-Zofiówka" colliery of the Jastrzębska Spółka Węglowa SA (see **Figure 1**). This company is the largest coking coal and coke producer in Poland and the entire European Union. The mining plants are located in southern Poland, in the Upper Silesian Coal Basin. The basic business of the company consists of the production and sales of hard coal (mainly coking coal), coke, and by-products. Maintaining coal and coke production at the quantitative and qualitative level required by customers is a crucial issue for the company (**Jastrzębska Spółka Węglowa SA, 2013**).

The mine field of KWK „Borynia-Zofiówka", "Zofiówka" Mining Plant – "Jastrzębie Górne 1" is situated in the southern-western part of the Upper-Silesian Coal Field. From an administrative point of view, the colliery area is situated in the area of the city of Jastrzębie Zdrój, the towns of Jastrzębie Bzie and Jastrzębie Szeroka, two municipalities: Pawłowice and Mszana as well as small parts of Pniówek and Gogołowa villages.

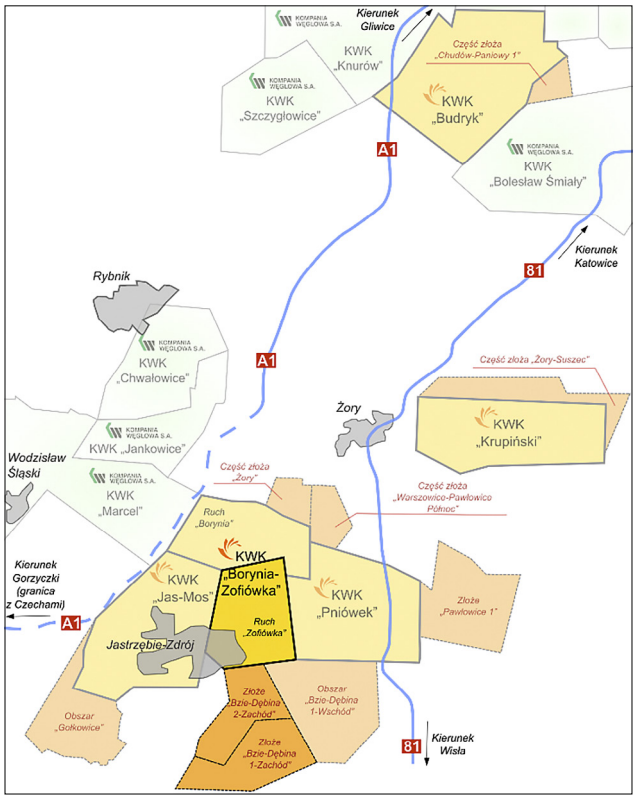

Figure 1: Location of "Borynia-Zofiówka" colliery – "Zofiówka" Mining Plant

The sampling of geological data under the aforementioned geological conditions took place during various stages of mine operation, including exploration of the deposit with surface boreholes, mine development, and the mining of coal seams using the longwall system. The data analysed specifically originated from surface boreholes, underground boreholes drilled from mine workings to upper or lower seams, as well as from headings or longwalls. These data were collected in-situ by mine personnel, and their absolute values are provided in **Table 1** below. These data serve as the input for the modelling process. The main goal was to discover patterns, trends, associations, or insight from vast amounts of data. The dataset was computationally time-consuming. During the research, the principle of random sampling was applied. Each data point in the dataset has an equal probability of being included in the sample. Then, random sampling is performed within each stratum to ensure representation from each group.

2.1. Indicators for estimation research parameters

The scientific base of neural network models is the fundamental building block called an artificial neuron or a perceptron. Artificial neurons are inspired by the biological neurons in the human brain and are designed to simulate their functionality. An artificial neuron takes multiple input signals, applies weights to each input, and combines them using a mathematical function. The weighted sum is then passed through an activation function, which determines the output of the neuron. The activation function introduces non-linearity into the model and allows neural networks to learn complex patterns and relationships (**Saraswathi and Tamilarasi, 2012; Yang, 2022**).

Neural networks consist of interconnected layers of these artificial neurons, forming a network of nodes. The most common type of neural network is the feedforward neural network, where the information flows in one direction, from the input layer through one or more hidden layers to the output layer. The connections between neurons have associated weights, which are adjusted during the training process to optimize the network's performance. This learning process, often referred to as backpropagation, involves iteratively comparing the network's predicted output with the desired output and adjusting the weights accordingly to minimize the prediction errors (**Wang et al., 2022**). Neural network models are based in forming similarity theorems in artificial neurons and their interconnections, which enable the networks to learn and make predictions based on the provided input data (**Vladyko et al., 2022a**).

In our case, widely used CRI (Coke Reactivity Index) and CSR (Coke Strength after Reaction) indicators are used, as they provide valuable information about the efficiency and performance of metallurgical coke. The

characteristics of coal, such as its rank, petrographic composition, maceral content, and mineral matter, have a significant influence on the CSR and CRI values of the resulting coke **(Díez et al., 2002)**.

CRI and CSR are used to forecast the price of coking coal and, as such, have a significant impact on the valuation of coal deposits and the economic assessment of mining projects (**Kopacz et al., 2020**). These indicators are often the main focus in predicting the quality of coking coal using various analytical methods (**North et al., 2018**).

To identify the factors that have the greatest influence on the main quality indicators (CRI and CSR) and to construct predictive models, we use the Group Method of Data Handling (GMDH) (**Ebtehaj, et al., 2015**).

2.2. Neural networks prediction models

In recent years, neural network models have become increasingly popular for their ability to accurately predict complex systems. However, the design and training of neural networks require extensive computational resources and can be time-consuming. To overcome these challenges, the Group Method of Data Handling (GMDH) has been proposed as a complementary approach for neural network modelling. GMDH is a data-driven method that utilizes a self-organizing approach to determine the best combination of input variables to predict a target output variable.

GMDH-based neural network models have been successfully applied to various fields, such as process modelling, time series prediction, and fault diagnosis (**Babets, et al., 2017**). The GMDH-based neural network models have demonstrated superior performance over conventional neural network models in terms of prediction accuracy, robustness, and generalization capability. One of the advantages of GMDH is its ability to automatically select the best subset of input variables for the model, which reduces the complexity of the model and improves its interpretability (**Abdolrahimi et al., 2014**).

In addition to GMDH, meta-heuristic optimization algorithms such as genetic algorithm and particle swarm optimization have been used to optimize the hyperparameters of GMDH-based neural network models. These approaches have been shown to further improve the accuracy of the models by optimizing the model architecture and parameter settings (**Dodangeh, et al., 2020; Nariman-zadeh and Ali, 2009**).

2.3. Group Method of Data Handling brief description

Group Method of Data Handling is based on the algorithm, which is a data-driven modeling technique developed by the Ukrainian scientist, A. Ivakhnenko (**Ivakhnenko, 1968**). In this article, the problem of structural-parametric identification, or the construction of models based on experimental data, can be reduced to finding the extremum of a certain criterion CR among a set of different models $\Im$.

$$f^* = \arg\min_{f\in\Im} CR(f) \tag{1}$$

In addition, the following details are required: specifying the type and extent of the initial information; indicating the class of reference functions (operators) that form the set $\Im$; defining the approach for generating models f and the corresponding parameter estimation method; selecting a criterion for comparing models; specifying the optimization method for minimizing the criterion function (CR). To provide further clarity, let's assume that a dataset W=[XY] is given, comprising N observation points, forming a matrix X = {xij, i=1,...,N; j=1,...,m}, and a vector Y = (y1,..., ym)T, where N ≥ m.

The method is founded on a thorough search approach, involving sequential experimentation of models selected from a pool of potential models based on a predetermined criterion. The majority of Model Selection algorithms utilize polynomial reference functions. The overall connection between input and output variables is represented in the form of a Volterra functional series, with its discrete counterpart known as the Kolmogorov-Gabor polynomial (**Madala et al., 1994**).

$$y = a_0 + \sum_{i=1}^{M} a_i x_i + \sum_{i=1}^{M}\sum_{j=1}^{M} a_{ij} x_i x_j + \\ + \sum_{i=1}^{M}\sum_{j=1}^{M}\sum_{k=1}^{M} a_{ijk} x_i x_j x_k \tag{2}$$

here $X(x_1, x_2,\ldots x_m)$ – input variables; $A(a_1, a_2,\ldots a_m)$ – coefficients of terms.

In general, the solution process of the structural-parametric identification problem (1) involves the following key stages:

1. Defining the dataset acquired from passive or active experiments, along with any available prior information.
2. Selecting or specifying the class of reference functions and performing data transformation.
3. Generating diverse model structures within the chosen class $\Im$.
4. Estimating the parameters of the generated structures and constructing the set F.
5. Minimizing the given criterion CR(f) and determining the optimal model f.
6. Assessing the adequacy of the obtained optimal model.
7. Making a decision to terminate the process.

In general, the task of identification involves constructing a set of models with varying structures based on the data sample:

$$\hat{y}_f = f(X, \hat{\theta}_f) \tag{3}$$

and finding the optimal model based on a certain criterion:

$$f^* = \arg\min_{f\in F} CR(y, f(X, \hat{\theta}_f)) \tag{4}$$

where $\hat{\theta}_f$ represents the parameter estimates.

The complexity of the model structure is evaluated by considering the number of polynomial terms employed. The exhaustive procedure entails calculating the criterion while systematically altering the model's structure.

The distinguishing features of GMDH algorithms compared to other algorithms for structural identification and best regression selection are as follows (**Müller J.A., 2000**):

Utilization of an external criterion based on data sample division, which is relevant to the task of constructing predictive models while reducing the requirements for the initial information volume.

Significantly greater diversity of structure generators: employing full or reduced enumeration of structure variations in regression algorithms and employing original multi-order iterative procedures.

Higher degree of automation - it is sufficient to input the initial data and specify the external criterion.

External and internal criteria are employed in GMDH algorithms. An internal criterion is computed using the entire dataset, while an external criterion is calculated using new information that was not used for estimating the model coefficients. Typically, the dataset is divided into a training set and a checking set, with common ratios being 50:50, 70:30, or 80:20. The training set is utilized for estimating model coefficients, while the checking set is used to assess the model structure and its ability to handle new data. The external criterion aims to identify a model structure that remains optimal when additional observations from the object are acquired.

This paper employs two modifications of the GMDH algorithm: GMDH-based neural network and GMDH-based stepwise forward selection. We will examine the structure of the input and output data, as well as the algorithms for both modifications.

Input:

- Training dataset with N samples and m input variables, X.
- Corresponding target output variables, Y.
- Maximum number of input variables, M.
- Maximum number of layers, L.

Output:

- Trained GMDH-based model.

Special software GMDH Shell was used to process the data and obtain relevant results. This software, also known as Group Method of Data Handling Shell, is used for data analysis, modeling, and forecasting. It starts with generating a pool of potential models using a combination of input variables. It then evaluates the performance of each model and selects the best-performing ones. The selected models are further refined by adding or removing input variables, and the process continues until an optimal model is achieved.

Software GMDH Shell utilizes a self-organizing approach to model building, meaning it automatically selects the most relevant input variables and constructs a model based on the available data. The algorithm aims to minimize the error between the predicted output and the actual output values by iteratively adjusting the model structure. It is a powerful tool for data analysis and modeling, particularly useful in situations where the underlying relationships in the data are complex or not well-defined. It automates the model-building process and can handle large datasets efficiently.

2.4. The algorithm for a GMDH-based implementation

The GMDH-based implementation is divided into two separate segments. The algorithm for a GMDH-based neural network:

- Initialize the network with a single-layer model using all input variables.
- For each layer, generate all possible combinations of input variables up to M.
- Evaluate the performance of all candidate models using a validation set.
- Select the best model with the lowest validation error.
- If the maximum number of layers has not been reached, repeat steps 2-4 for the next layer.
- Output the final trained model.

Algorithm for a GMDH-based stepwise forward selection:

- Initialize the model with a single-layer model using the input variable with the highest correlation coefficient with the target output variable.
- For each layer, add the input variable with the highest correlation coefficient with the target output variable among the remaining input variables.
- Generate all possible interactions between the selected input variables and evaluate their performance using a validation set.
- Select the best combination of input variables and interactions with the lowest validation error.
- If the maximum number of layers has not been reached, repeat steps 2-4 for the next layer.
- Output the final trained model.

The GMDH-based neural network is a self-organizing approach, which means that it automatically selects the optimal combination of input variables and their interactions to construct a model with high accuracy and low complexity. The validation set is used to evaluate the performance of candidate models during the training process and prevent overfitting.

3. Results and discussion

While working in a managerial position at Jastrzębska Spółka Węglowa SA, the author of this article noticed that the projected performance indicators of the company deviated significantly from the final economic results

Table 1: Data structure

Coke Reactivity Index (CRI), %	Coke Strength after Reaction (CSR) %	Coal density (DA), g/cm³	Vitrinite reflectivity (RO)	Vitrinite content (VT), %	Liptinite content (L), %	Inertinite content (I), %	Content of mineral parts (M), %	Ash content (AA), %	Coal caking index (RI)	Free pulsing (SI)	Dilatation (B)	Phosphorus content (PA), %	Sulphur content (S), %	Volatile content (VF), %	Contraction, (A)	Calorific value (QIA), kJ/kg	Bound moisture content (WA), %	Chlorine content (CL), %	Ash content in dry sample (AD), %
27.1	65.8	1.33	1.21	64	3	28	5	6.94	84	8.5	160	0.128	1.02	24.48	27	32506	0.53	0.12	6.98
28.5	65.2	1.36	1.29	51	5	39	5	9.93	78	8	34	0.042	0.52	21.8	30	31168	0.64	0.07	9.99
82.1	12.1	1.28	1.36	66	4	28	2	3.24	79	8	44	0.011	0.32	21	30	34081	0.66	0.08	3.26
22.2	69.6	1.33	1.21	66	9	23	2	6.72	84	8.5	137	0.179	0.83	24.37	26	32659	0.6	0.1	6.76
52.6	41.6	1.31	1.37	61	4	33	2	3.92	72	6.5	10	0.006	0.34	19.73	26	33544	0.62	0.09	3.94

Table 2: Validation criterion for top-ranked models

Model type	RMSE for CRI	RMSE for CSR
Neural network	7.9	8.5
Linear model	10.5	10.9
Nonlinear model	8.1	8.9

of the mine's operation. This was caused, among other things, by the uncertainty in the determination of production capacity, the size of resources and the quality of the final products. Therefore, it was hypothesised that there are priority factors that are key to the economic performance of the mine. In order to improve the operating cycle of the process chain, it is worth identifying and first exploring the possibility of improving the company's performance in these key areas. Therefore, it is necessary to find appropriate mathematical mechanisms to rank the mentioned.

The use of new methods for predicting indicators, particularly those relevant to product quality, should allow a better assessment of the value of a deposit and, as a result, a more accurate determination of the economically recoverable reserves. This approach could also be used as an effective mechanism for determining economic efficiency indicators for mining companies.

Statistical processing of functioning data of the Jastrzębska Spółka Węglowa SA was performed in order to carry out the necessary research. The data were processed and summarised into 435 observations. The influence of 18 input variables on 2 resultant indicators (CRI and CSR) was examined. The structure of the data is shown in **Table 1**. These data were accepted for further formation of neural networks for simulation of production processes and determination of mining priorities in Jastrzębska Spółka Węglowa SA.

A total of three models were calculated for each CRI and CSR indicator:

GMDH-based neural network model.

GMDH-based stepwise forward selection Linear model.

GMDH-based stepwise forward selection Nonlinear model.

The values of the validation criterion are shown in **Table 2**. The top-ranked model has the smallest criterion value (the lower the value, the higher the adequacy of the model).

As a validation criterion the Root-Mean-Square Error (RMSE) was used (5). This criterion is frequently used to measure the differences between values predicted by a model and the values observed.

$$RMSE = \sqrt{\frac{\sum_i^N \left(\widehat{y_i} - y_i\right)^2}{N}} \tag{5}$$

Where:

N – number of observations;

$\widehat{y_i}$ – predicted values;

y_i – observed values.

GMDH-based neural network model for CRI indicator:

$$\begin{gathered} CRI = -2.29954 + N370*0.475375 - \\ - N370*N11*0.0403961 + N370\text{^}2*0.0143235 + \\ + N11*0.629673 + N11\text{^}2*0.0245661 \end{gathered}$$

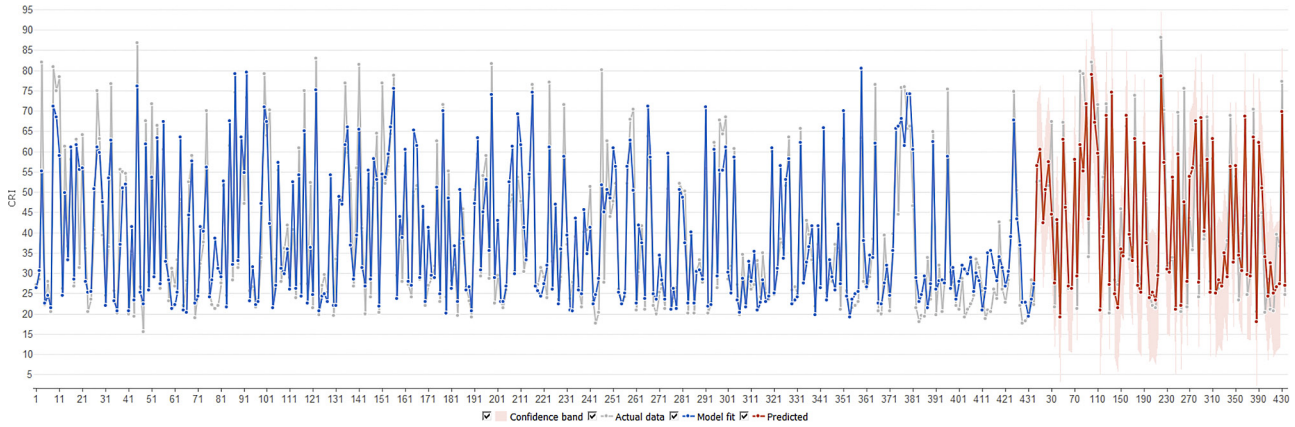

Figure 2: Actual data and model fit for CRI indicator

The definition of the input parameters used in the formula for calculating the CRI is given in Appendix A.

In GMDH-based neural network models, the parameters N represent submodels (best candidate models) from previous layers. Some of them depend solely on the input data (e.g. N812, N707, etc.), while other models in higher layers include the generated models from the preceding layers (e.g. N11, N25, etc.). The final predictive model can be formulated as a dependency solely on the input data by sequentially substituting the submodels from previous levels into the models of subsequent levels. The plot of actual data and model fit for CRI indicator is represented in **Figure 2**.

Accuracy of the model: coefficient of determination R^2=0.81 for training data set and R^2=0.73 for validation data. Correlation R=0.9 and R=0.86 for training and validation data respectively. Mean absolute error (6) MAE=5.9 for training data set and MAE=7.1 for validation data

$$MAE = \frac{\sum_i^N \left| \left(\widehat{y_i} - y_i \right) \right|}{N} \tag{6}$$

where:

N – number of observations;

$\widehat{y_i}$ – predicted values;

y_i – observed values.

The GMDH algorithm divides the input data into two sets: the training set and the validation set. The model is trained on the training data, which involves determining the model structure and estimating the regression coefficients. The validation set is used to test the model's stability with respect to new data. In essence, predictions for the training set are based on the data used to train the model, while predictions for the validation set are made using a model trained on a different data subset. Therefore, it is advisable to consider two correlation coefficients: one for the training subset (shown in blue in the figure) and another for the validation subset (represented by the red dashed line).

To assess the significance of different factors, a methodology is employed wherein each variable in the model is individually substituted with its mean value. The resulting Root Mean Square Error (RMSE) of this "new" model is then computed. The original model's error is regarded as having a zero percent impact on the RMSE, while a scenario where all variables are replaced with their means represents a 100% impact. It is worth noting that the impact can exceed 100% when variables in the model interact with each other through multiplication or squaring. Additionally, a small negative percentage may arise if a variable proves to be essentially irrelevant for the model's predictions.

Impact on RMSE (7) is a percentage value it is calculated as

$$I = \frac{R_i - R_0}{R - R_0} \cdot 100\% \tag{7}$$

where:

R_i – RMSE of the variable we consider;

R_0 – zero-impact RMSE;

R – RMSE of a model where all variables are replaced with mean.

The importance of factors in GMDH-based neural network model for CRI are shown in **Figure 3**.

#	If replaced with mean	Impact on RMSE	Bars	RMSE
1	B	47,25%		13,0069
2	VF	44,25%		12,6847
3	PA	25,37%		10,6558
4	AA	14,02%		9,43649
5	CL	13,30%		9,35857
6	S	11,84%		9,20213
7	RO	6,74%		8,65341
8	I	5,03%		8,47033
9	QIA	3,67%		8,32379
10	AD	2,67%		8,21581
11	DA	2,17%		8,16218
12	VT	1,21%		8,05962
13	A	1,05%		8,04218

Figure 3: Importance of variables in neural network model for CRI

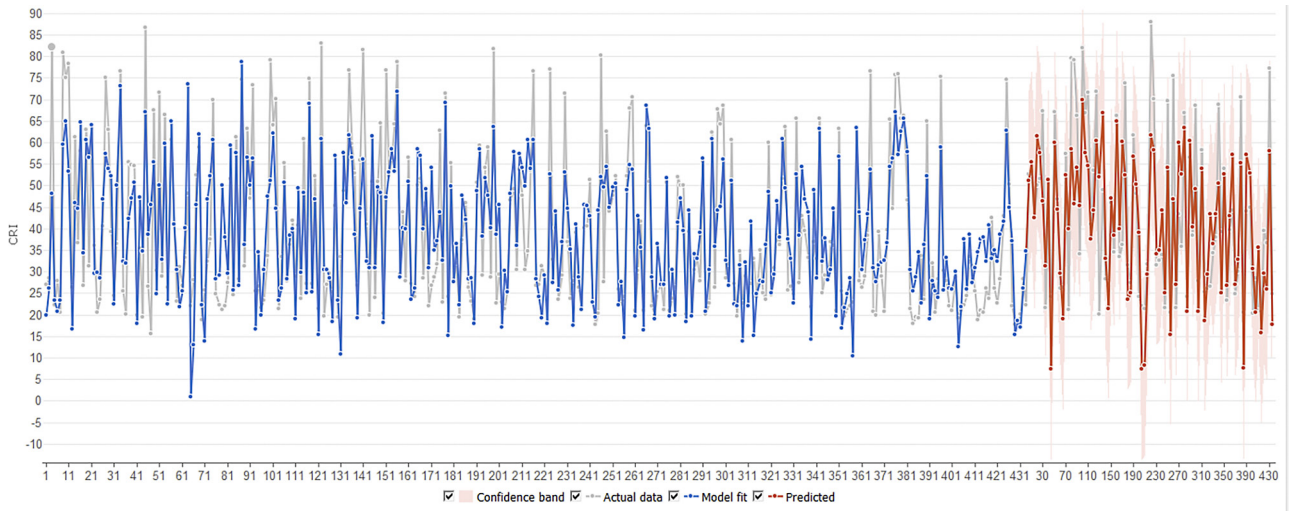

Figure 4: Actual data and model fit for CRI Linear model

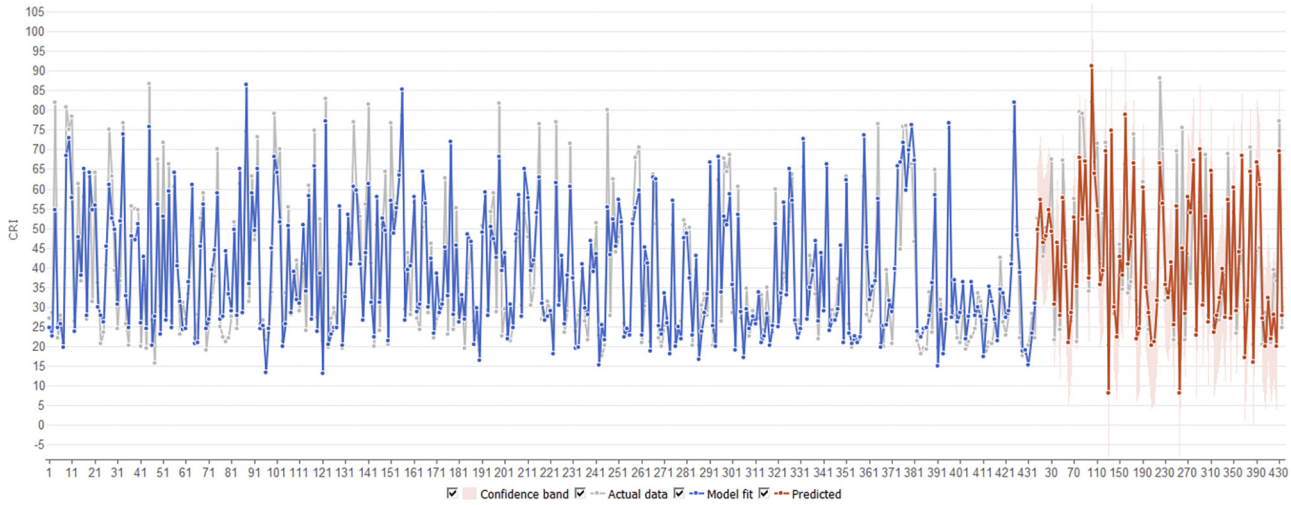

Figure 5: Actual data and model fit for CRI Nonlinear model

Analysis of the influence of the factors on the resulting variable shows that B (Dilatation), VF (Volatile content, %) and PA (Phosphorus content, %) have the greatest influence.

Below is the mathematical description of the linear and nonlinear models for the CRI indicator, as well as the neural network, linear and nonlinear models for the CSR indicator.

GMDH-based stepwise forward selection Linear model for CRI:

CRI = –114.323 + B*(-0.17206) + AA*(–3.01198) +
+ VF*6.56411 + SI*(-2.35426) + RO*58.8028 +
+ CL*79.8182 + PA*(–42.0338) + S*(–13.7553) +
+ A*(–0.544035) + RI*(–0.0547029).

The plot of actual data and model fit for CRI Linear model is represented in **Figure 4**.

GMDH-based stepwise forward selection Nonlinear model for CRI:

CRI = 215.31 + DA^(–1)*SI^(–1)*S^(–1)*
*(–118.485) + AA*A*CL^(–1)*(–0.00328318) +
+ PA*VF^(–1)*AD^(–1)*(–15331.9) +
+ B*VF^(–1)*QIA*0.000832805 +
+ SI^(–1)*S^(–1)*VF^(–1)*(–3594.5) +
+ DA*RO^(–1)*VF^(–1)*(–3138.08) +
+ L^(–1)*I*S*1.12353 + B*PA*VF^(–1)*11.8143 +
+ RO*B*PA*(–0.352688) +
+ AA*S^(–1)*A^(–1)*(–25.6526) +
+ B*CL^(–1)*AD*0.000771639 +
+ RO*B*QIA*(–3.31181e–05) +
+ SI^(–1)*S^(–1)*QIA*0.00925999 +
+ B^3*1.89042e–06 +
+ SI^(–1)*A*CL^(–1)*(–0.160241) +
+ I^(–1)*CL*AD^(–1)*(–9528.81) +
+ RI*S*VF^(–1)*(–7.35664) +
+ L^(–1)*I*B*(–0.00606229) +
+ I^(–1)*PA*S*1314.01 + RI*A^(–1)*CL*25.3936

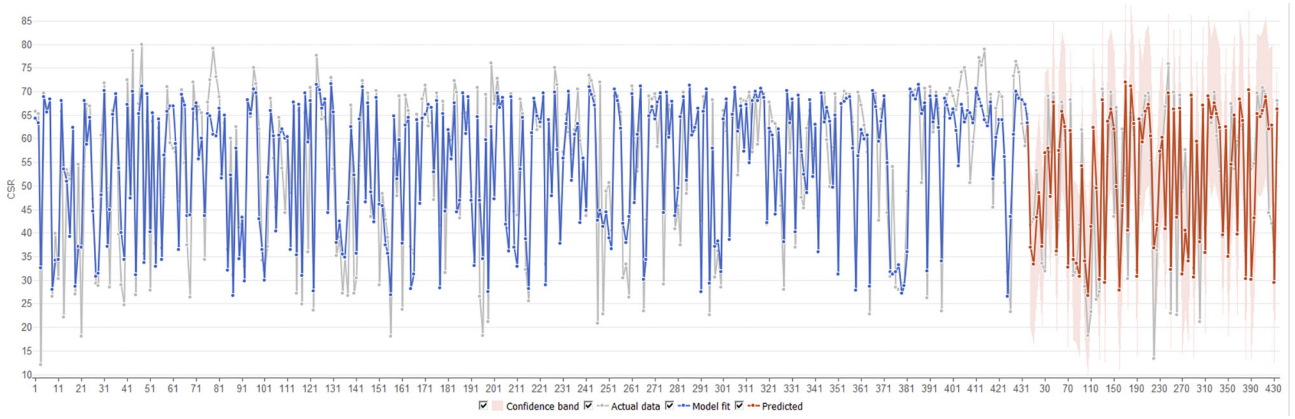

Figure 6: Actual data and model fit for CRI indicator

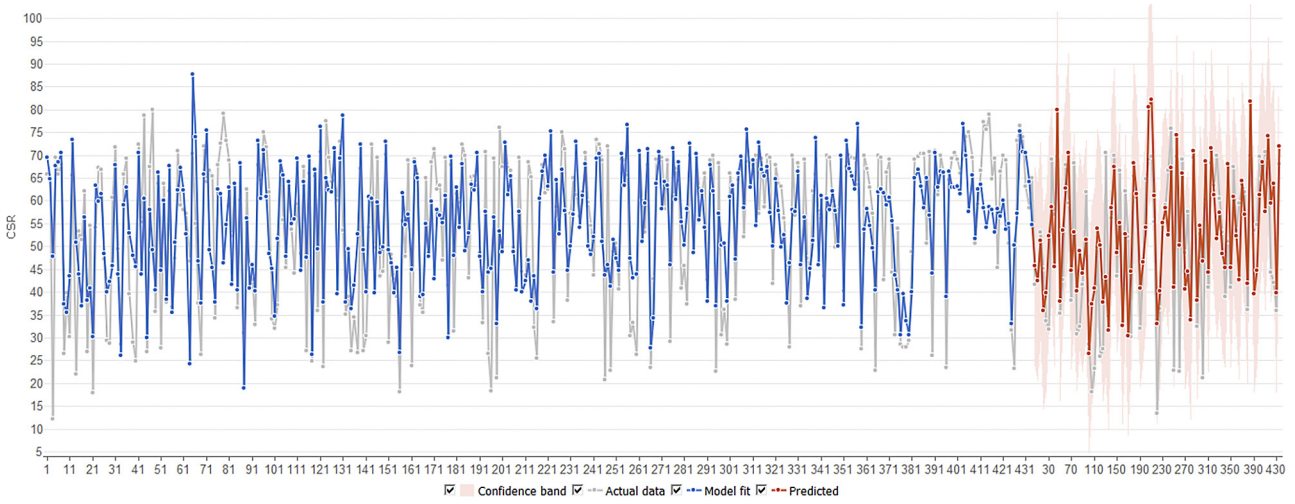

Figure 7: Actual data and model fit for CRI Linear model

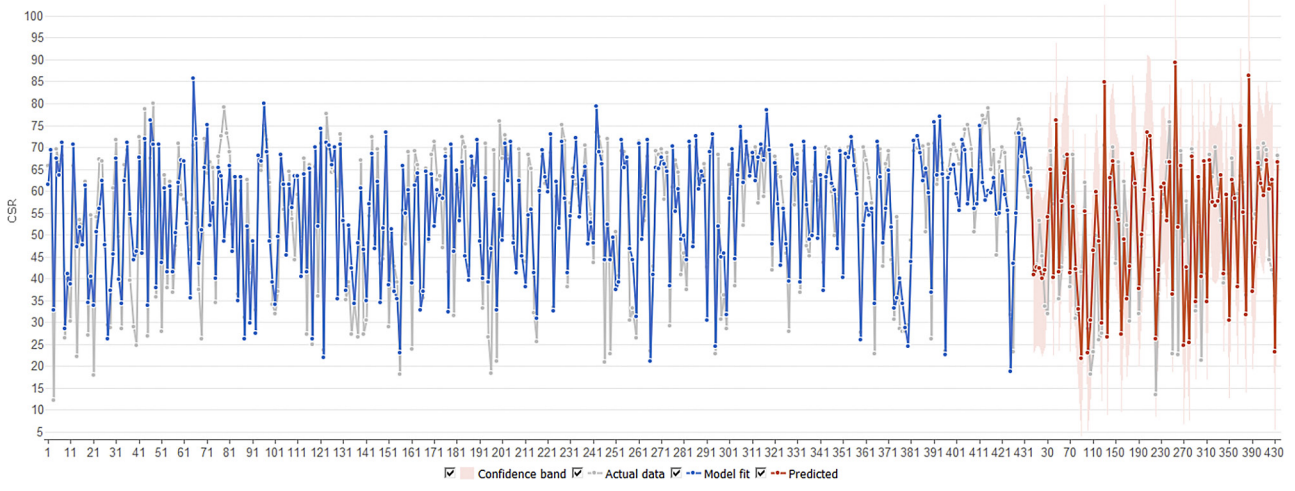

Figure 8: Actual data and model fit for CSR Nonlinear model

The plot of actual data and model fit for CRI Nonlinear model is represented in **Figure 5**.

GMDH-based neural network model for CSR indicator:

$$CSR = 9.94029 - N5*117.315 - N5*N6*3.69415 + + N5^2*3.70083 + N6*117.743$$

The definition of the input parameters used in the formula for calculating the CSR is given in Appendix B.

The plot of actual data and model fit for CSR indicator is represented in **Figure 6**.

GMDH-based stepwise forward selection Linear model for CSR:

Table 3: Accuracy of the created models

Accuracy parameter	Neural network for CRI	Linear model for CRI	Nonlinear model for CRI	Neural network for CSR	Linear model for CSR	Nonlinear model for CSR
coefficient of determination R^2 for training data	0.81	0.66	0.80	0.73	0.55	0.70
coefficient of determination R^2 for validation data	0.73	0.57	0.68	0.55	0.50	0.50
Correlation for training data	0.9	0.81	0.89	0.85	0.74	0.84
Correlation for validation data	0.86	0.77	0.84	0.76	0.72	0.75
Mean absolute error for training data	5.9	8.2	6.13	6.23	8.60	6.84
Mean absolute error for validation data	7.1	9.8	8.28	8.18	8.81	9.20

Table 4: Influence of input factors on the resulting indicators

Impact Rank	Neural network for CRI	Linear model for CRI	Nonlinear model for CRI	Neural network for CSR	Linear model for CSR	Nonlinear model for CSR
1	B	VF	VF	AA	VF	VF
2	VF	B	B	AD	B	PA
3	PA	AA	AA	B	AA	B

CSR = 196.517 + B*0.131879 + S*15.8306 +
+ VF*(-6.03398) + AA*2.23735 + A*0.692161 +
+ PA*46.056 + CL*(-78.1928) + +RI*0.027657 +
+ RO*(-51.8935) + SI*1.71879 + M*(-0.270236)

The plot of actual data and model fit for CSR Linear model is represented in **Figure 7**.

GMDH-based stepwise forward selection Nonlinear model for CSR:

CSR = –1070.89 + DA^(–1)*S^(–1)*QIA*
*(–0.001415) + SI*A*CL^(–1)*0.00375944 +
+ PA*S^(–1)*AD^(–1)*297.396 +
+ DA*S^(–1)*VF^(–1)*253.065 +
+ B*VF^(–1)*CL*28.5744 + RO^(–1)*
*VF^(–1)*QIA^(–1)*5.71811e+08 +
+ PA*S^(–1)*CL*(–52.1607) +
+ RO*VF*QIA*0.000579237 +
+ PA^(–1)*S^2*(–0.0845576) +
+ PA^(–1)*CL*AD^(–1)*0.460491 +
+ L^(–1)*PA*S*(–66.9696) +
+ VT^(–1)*SI*A*2.06247 +
+ M^(–1)*CL*AD^(–1)*364.371 +
+ I*SI*CL*(–0.470658) +
+ M^(–1)*AA^(–1)*WA*(–41.9513) +
+ VT^(–1)*B*PA^(–1)*0.00764403 +
+ S^(–1)*A^(–1)*CL*2517.41 +
+ VF*A^(–1)*CL*(–281.548) +
+ SI^(–1)*B*A*(–0.0398572) +
+ RI^(–1)*SI*B*0.976122

The plot of actual data and model fit for CSR Nonlinear model is represented in **Figure 8**.

Information about the accuracy (adequacy) of all the created models is summarized in **Table 3**.

Information about the influence of input factors on the resulting indicators CRI and CSR is summarized in **Table 4**.

Examining the input factors (see **Table 4**), in a broader context, it can be concluded that the B indicator (dilatation) has been included in all the models constructed, indicating a significant correlation between both indicators and this parameter. It is also noteworthy that most of the models with a significant influence on the output variable have included the VF (volatile matter content) and AA (ash content, %) parameters.

4. Conclusion

Based on the research provided, it can be concluded that Artificial Intelligence (AI) is a powerful tool for the mining industry, offering significant benefits and advancements. Mining technologies, such as machine learning and data analytics, enable mining companies to optimize various processes, such as exploration, mineral extraction, resource estimation, and equipment maintenance. By using AI algorithms, mining operations can improve efficiency and increase overall productivity. It can also help mining companies address environmental challenges by optimizing resource usage. It is important to note that the algorithms can assist in the efficient monitoring of operations. While AI offers immense potential in mining, challenges remain, including data quality and availability, the need for skilled personnel, and ethical considerations. Addressing these challenges will be critical to maximizing the potential of AI in mining and ensuring its responsible and sustainable implementation. Overall, the integration of AI in mining has

the potential to revolutionize the industry, unlocking new opportunities for efficiency, safety, sustainability, and productivity. By leveraging AI technologies, it is possible to optimize operations, and navigate the complexities of the industry in a rapidly changing global world.

The examination of the developed models shows a favourable correlation for both CRI and CSR indicators concerning the training data set. However, it should be noted, that the models constructed for the CRI indicator have better predictive properties. Furthermore, among the three types of models developed, the models built using the neural network algorithm have demonstrated the most favourable predictive properties.

The created neural networks for the conditions of the mines of Jastrzębska Spółka Węglowa SA made it possible to process the statistical data of the company and to identify the priority factors determining the quality indicators of the final products. Of the 18 parameters analysed, three factors have a significant influence on the formation of coking coal indicators: dilatation, volatile matter content and ash content.

Such an approach makes it possible to predict the most important indicators of coke quality on the basis of a larger number of coal quality parameters and to eliminate parameters that have practically no influence on the value of the final product. The results of the study can also be used to assess the value of the deposit and to better plan its exploration by identifying which coal quality parameters are particularly relevant to the value of the future mining project.

In further research, the author will try to highlight the results of the implementation of AI systems in Jastrzębska Spółka Węglowa SA and other mining companies. It's important to emphasize that research in this area involves collaboration between data scientists, mining engineers, and domain experts to ensure that neural networks are tailored to the specific needs and challenges of the mining industry. Moreover, given the critical nature of mining operations, the implementation of neural networks must undergo rigorous testing and validation to ensure safety and reliability.

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SAŽETAK

Predviđanje ključnih parametara kvalitete koksnoga ugljena u stvarnome vremenu pomoću neuronskih mreža i umjetne inteligencije

Koks visoke kvalitete ključna je sirovina u metalurškoj industriji. Svojstva ugljena imaju velik utjecaj na kvalitetu proizvedenoga koksa, a time i na vrednovanje ležišta ugljena i ekonomsku ocjenu rudarskih projekata. Predviđanje kvalitete ugljena za koksiranje omogućuje optimizaciju proizvodnih procesa uključujući planiranje i upravljanje procesima te rano otkrivanje problematične kvalitete. U ovoj studiji korištenjem načela pametnoga rudnika predlaže se određivanje kvalitete ugljena na temelju kombinacije rudarsko-geoloških uvjeta ležišta mineralnih sirovina i njegovih pokazatelja kakvoće. Utvrđeni su mogući međuodnosi između kvalitete ugljena u ležištu i svojstava konačnoga proizvoda. Neuronskom mrežom utvrđuje se prioritet pojedinih pokazatelja koji imaju znatan utjecaj na kvalitetu koksnoga ugljena. Važan je dio istraživanja njegova praktična provedba u kompaniji Jastrzębska Spółka Węglowa SA. Metodom uzorkovanja i statističkom obradom podataka dobiveni su kvalitativni i kvantitativni parametri koksnoga ugljena za svaki rudnik kao što su: stupanj metamorfizma, debljina, odstupanje hlapljivih tvari, prisutnost fosfora, sadržaj pepela itd. Pomoću grupne metode obrade podataka uspoređeni su pokazatelji kvalitete ovisno o prioritetu utjecaja na konačna svojstva ugljena za koksiranje. Na temelju dobivenih rezultata pokazalo se da svi pokazatelji kakvoće ugljena nemaju znatan utjecaj na kvalitetu konačnoga proizvoda. Studija pokazuje da je moguće predvidjeti glavne pokazatelje (CRI – indeks reaktivnosti koksa, CSR – čvrstoću koksa poslije reakcije s CO_2) kvalitete koksa korištenjem neuronskih mreža na temelju većega broja parametara kvalitete ugljena i eliminirati parametre koji nemaju praktički nikakav utjecaj. na vrijednost konačnoga proizvoda. Ova se metoda također može koristiti za poboljšanje rezultata ekonomskoga vrednovanja ležišta i za bolje planiranje istražnih i rudarskih radova.

Ključne riječi:
koksni ugljen, kvaliteta ugljena, neuronska mreža, umjetna inteligencija, grupna metoda obrade podataka (GMDH)

Author contribution

Artur Dyczko (PhD.) provided a description of the problem and analysis of the drawbacks of technologies; development of approaches to the development of the research methodology, performance the preliminary calculation; analysis of research results; developing the algorithm for calculation and determination of parameters; description of the research and all other elements of the article.