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Prediction of the main caving span in longwall mining using fuzzy MCDM technique and statistical method

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Abstract

Immediate roof caving in longwall mining is a complex dynamic process, and it is the core of numerous issues and challenges in this method. Hence, a reliable prediction of the strata behavior and its caving potential is imperative in the planning stage of a longwall project. The span of the main caving is the quantitative criterion that represents cavability. In this paper, two approaches are proposed in order to predict the span of the main caving in longwall projects. Cavability index (CI) is introduced based on the hybrid multi-criteria decision-making technique, combining the fuzzy analytical network processes (ANP) and the fuzzy decision-making trial and evaluation laboratory (DEAMTEL). Subsequently, the relationship between the new index and the caving span is determined. In addition, statistical relationships are developed, incorporating the multivariate regression method. The real data for nine panels is used to develop the new models. Accordingly, two models based on CI including the Gaussian and cubic models as well as the linear and non-linear regression models are proposed. The performance of the proposed models is evaluated in various actual cases. The results obtained indicate that the CI-Gaussian model possesses a higher performance in the prediction of the main caving span in actual cases when compared to the other models. These results confirm that it is not possible to consider all the effective parameters in an empirical relationship due to a higher error in the prediction.

Keywords: *Main Caving Span, Cavability Index, Longwall, Multi-Criteria Decision-Making, Regression Analysis.*

1. Introduction

In longwall mining, a part of the overburden loses its natural support due to extraction and advancement of the extraction face. Once a certain unsupported span is reached, the nether strata of the immediate roof fractures, and subsequently, falls. This distance, which is from the barrier pillar to the caving point, is the main caving span (first weighting interval or main fall distance), as shown by l_s in Figure 1. After this step, as mining processes further, the upper strata will break periodically, leading to the periodic caving span (periodic weighting interval or periodic fall distance) (l_p in Figure 1). Generally, the main caving span is greater than the periodic distance. In the caving process, caved rocks provide a support for the upper layer and transfer their loads to the floor. This reduces stresses at abutments and ahead of the longwall face [1-2].

A proper caving guarantees the success of this mining method, while delayed or/and poor caving will lead to severe consequences such as face jamming, rock burst on the face, and airburst [3]. A thorough understanding of strata mechanics and caving mechanism is imperative in the planning stage for subsidence and ground control design, stability prediction of face, roadways and gates, determination of the load capacity of longwall shields, designing the pillars, and length of longwall panels.

In the literature, there are a number of empirical and analytical models to predict the main caving span. The empirical models have been developed based on the field experiments and the actual field data. A number of them have proposed a quantitative relationship to predict the main caving span [1, 4-8], and some others have provided both options of the qualitative assessment of cavability and predicted relationship of the main span fall [7, 9-11]. Analytical models are typically based upon theoretical approaches such as the plate-beam theory for prediction of the main caving span [12-15].

A critical review of different approaches in the main caving span prediction has revealed that the empirical methods which were developed on the basis of databases are not practical for several cases. On the other hand, the analytical methods have various assumptions, leading to reduction in their practical applications. In order to overcome these drawbacks, this paper proposes two approaches in order to predict the span of the main caving in the form of the knowledge-based and data-based models. In the first one, an empirical index was introduced using the hybrid fuzzy multi-criteria decision-making (MCDM) technique. Statistical relationships were developed via multivariate regression in the second approach, incorporating databases of worldwide longwall experiments. Finally, the performance of the proposed models was evaluated in the prediction of the main caving span for actual cases.

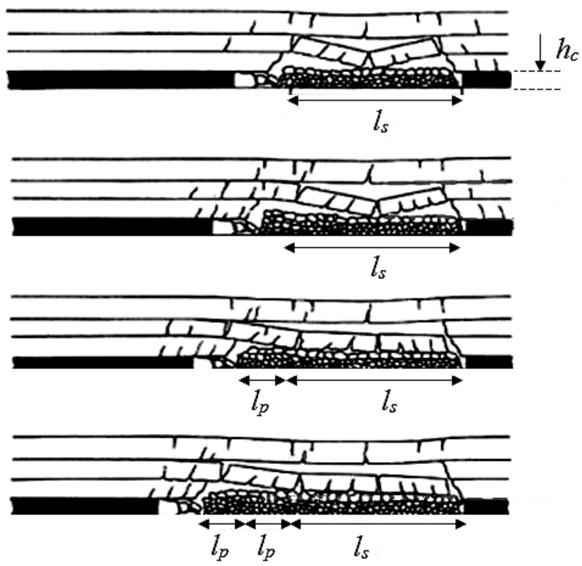


Figure 1. Main and periodic distance in caving process [1].

2. Methods and materials

2.1. Methodology

Two approaches, namely hybrid fuzzy MCDM and regression technique, were applied to predict the span of the main fall. The flowchart of developing and evaluating the proposed models is shown in Figure 2.

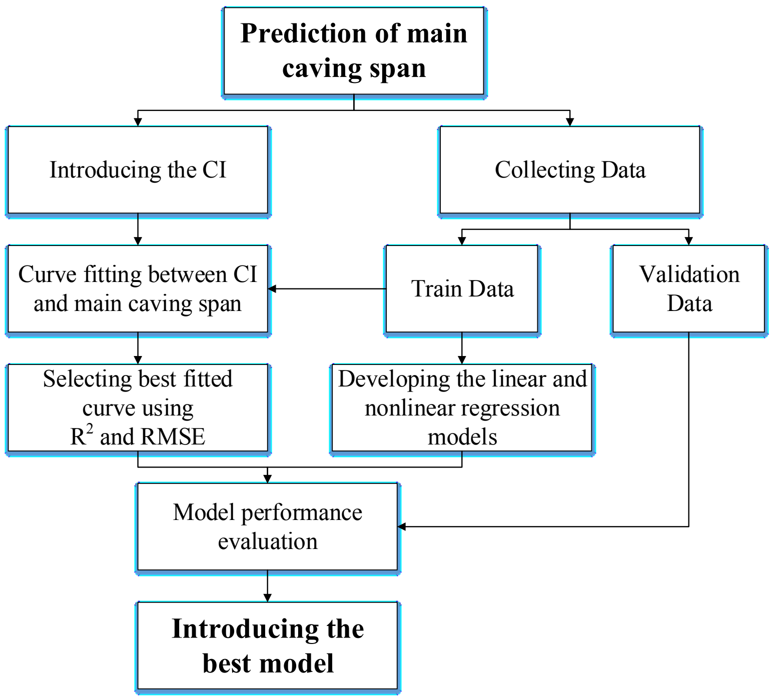


Figure 2. Flowchart of developing new models for prediction of main caving span.

In the first approach, the cavability index (CI) was introduced using a combination of the fuzzy analytical network process (ANP) and the fuzzy decision-making trial and evaluation laboratory (DEMATEL) methods. ANP is the general form and extension of the AHP method that provides a general framework to deal with complex real problems in which there are independencies within a cluster and among the different clusters [16]. ANP forms a supermatrix of problem, in which the inner and outer dependencies are merged together to calculate the weight of each parameter. DEMATEL is a robust method used in formulating the sophisticated structures that models the interdependent relationships within a set of criteria under consideration [17]. In this paper, the inner-dependence among parameters was evaluated by the fuzzy DEMATEL. Outer-dependencies as well as weighting of clusters were determined using the fuzzy ANP procedure through pairwise compression. Based upon this hybrid method, a classification system was developed, in which the parameters were rated to calculate CI. Finally, the relationship between the new index and the caving span of actual cases was determined using the curve fitting toolbox of the MATLAB software, and accordingly, the best-fitted curve was selected. In order to validate the model, the caving span and performance of the proposed approach were evaluated.

In the second approach, the statistical analysis was used to develop the regression relationship for predicting the caving span. The input variables were selected based on the literature data, and the main caving span was regarded as the output variable. Using the data of actual panels, the linear and non-linear multivariate regression relationships were developed. For this purpose, the package ''Statistical Package for Social Science (SPSS)'' was used. Validation of the proposed models in the train step was conducted by considering 5 tests including t-test, F-test, assumptions of errors independence, errors normality, and linearity of independent variables.

The T-test is a univariate hypothesis test applied when standard deviation is not known and the sample size is small, while the F-test is a statistical test that determines the equality of variances of two normal populations. The error independence is evaluated via the Durbin–Watson test. Error normality is controlled through comparing the distribution of error with normal distribution and scatter plot, in which the regression standardized residual is the y-axis and the regression standardized predicted value is the x-axis. The linearity of independent variables in regression is limited by controlling the variance inflation factor (VIF) and tolerance [18-19].

Finally, performance of the new linear and non-linear multivariate regression models was evaluated by the actual field data. In the validation step, for both approaches, their performances were evaluated using three performance criteria including coefficient of determination (R^2), root mean square error (RMSE), proportion of variance accounted for (VAF), and mean absolute percentage error (MAPE). These criteria are as follow:

$$R^2 = 100\left[\frac{\left(\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})(y_{pred}-\bar{y}_{pred})\right)^2}{\sqrt{\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})^2\sum_{i=1}^{N}(y_{pred}-\bar{y}_{pred})^2}}\right] \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{meas}-y_{pred})^2} \quad (2)$$

$$VAF = 100\left[1-\frac{\operatorname{var}(y_{meas}-y_{pred})}{\operatorname{var}(y_{meas})}\right] \quad (3)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_{meas}-y_{pred}}{y_{meas}}\right|\times 100 \quad (4)$$

where

y_{meas} is the measured value,

y_{pred} is the predicted value,

$\bar{y}_{meas}$ is the mean of measured values,

$\bar{y}_{pred}$ is the means of predicted values, and

var is the variance.

2.2. Database

A database including the data for twelve longwall panels around the world was collected. Among them, nine panels were selected randomly as the training cases to investigate the relationship between CI and the main caving span as well as for developing the regression relationships. The rest were considered as the validation cases to evaluate and to compare the performance of the two approaches (Table 1).

Table 1. Relevant data of used longwall panels [3, 11, 20-25].

No.	Continent	Country	Mine/Coalfield	Panel
1	Asia	Iran	Parvadeh 1	E0
2		India	GDK 10A Incline mine	3D2
3		India	GDK 10A Incline mine	No.14
4		India	GDK 10A Incline mine	3A
5		India	Moonidih	A4
6		India	PVK 5*	21
7	Europe	Germany	Ruhr mining district*	-
8		Norway	Svea Nord	C6
9	Africa	South Africa	Highveld Coalfield	-
10		South Africa	Malta Colliery	No.1
11		South Africa	New Denmark Colliery*	No.509
12	America	USA	CONSOL Central Appalachian	8-R

3. Proposed models

3.1. Cavability index (CI)

In order to introduce CI, the most significant parameters involved in the caving process were determined on the basis of the literature, as shown in Figure 3. Then the supermatrix of problem was established as follows:

$$
\begin{array}{r c}
 & \begin{array}{ccc} \text{Cavability (goal)} & \text{Categories} & \text{Parameters} \end{array} \\
\begin{array}{r} \text{Cavability (goal)} \\ \text{Categories} \\ \text{Parameters} \end{array} &
\begin{bmatrix} 0 & 0 & 0 \\ W_{21} & W_{22} & 0 \\ 0 & W_{32} & W_{33} \end{bmatrix}
\end{array}
$$

In this supermatrix, W_{22} and W_{33} are the inner inner-dependency matrices that were evaluated using fuzzy DEMATEL. In addition, W_{21} and W_{32} are the outer-dependencies that were determined using fuzzy ANP. For this purpose, some questionnaires were distributed among seventeen academics and industrial experts, and their opinions and judgments were collected. After placing the matrices W_{22}, W_{33}, W_{21}, and W_{32}, the weighted supermatrix was derived by equating the normalized summation of each column to 1. The parameters weights in this process were determined after calculation of the limit supermatrix. Thus the weighted supermatrix was raised to the limiting powers, calculating the ultimate parameters weights as listed in Table 2.

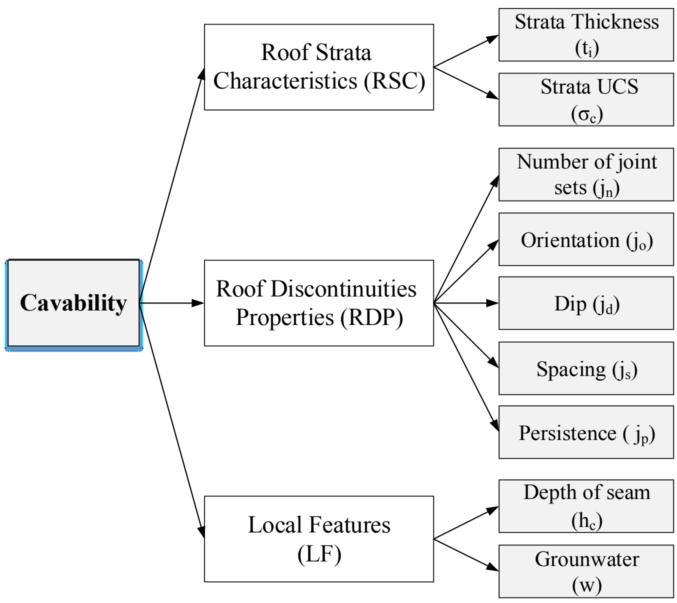


Figure 3. Significant parameters of caving roof strata.

Table 2. Parameters weights in cavability index.

No.	Parameters	Weight%
1	Strata thickness	12
2	Strata UCS	13
3	Number of joint set	12
4	Joint dip	10
5	Joint orientation	10
6	Joint spacing	11
7	Joint persistence	10
8	Depth	11
9	Groundwater flow	11
	Sum	100

In order to introduce CI, all the parameters involved were classified into five classes (with the exception of joint persistence, which was classified into three classes) in accordance with their role in the caving on the basis of the literature and standard guidelines. A corresponding rate from 0 to 4 was assigned to each class. Table 3 shows the proposed rating table of the effective parameters in caving. It is noted that the coal strata are grouped into several composite layers, which have different and complex mechanical and caving behavior. Different strata properties may influence the immediate roof properties. Therefore, the equivalent immediate roof strength (EIRS) was defined as the thickness-weighted average of roof the strata uniaxial compressive strength as:

$$EIRS = \frac{\sum_{i=1}^{n} t_i \times \sigma_{c_i}}{\sum_{i=1}^{n} t_i} \tag{5}$$

where

t_i is the thickness of the ith stratum (m),

σ_{c_i} is the UCS of the ith stratum (MPa), and

n is the number of stratum within the immediate roof.

It should be noted that the weight of EIRS is the total weight of strata characteristics (i.e. the weight of strata UCS plus strata thickness which will be equal to 25).

Effects of joint orientation and dip in Table 3 are determined based on Table 4.

Table 3. System classification parameters.

No.	Parameters	Rating				
		0	1	2	3	4
1	EIRS (Mpa)	> 250	250-100	100-50	50-25	< 25
2	Number of joint sets	Massive	Only bedding planes	Bedding planes plus a joint set	Two joint sets	Three or more joint sets
3	Joint orientation and dip	Very unfavorable	Unfavorable	Fair	Favorable	Very favorable
4	Joint Spacing (m)	> 1.8	1.8-0.6	0.6-0.2	0.2-0.06	< 0.06
5	Joint persistence (m)		0-1	1-3	> 3	
6	Depth (m)	< 100	100-300	300-600	600-1000	> 1000
7	Groundwater flow	None	None visible	Light seepage/dripping	Steady seepage/flowing	Heavy seepage/gushing

Table 4. Expression of joint orientation and dip.

Strike perpendicular to panel axis				Strike parallel to panel axis		Irrespective of strike
Drive with dip		Drive against dip				
Dip 45°-90°	Dip 20°-45°	Dip 45°-90°	Dip 20°-45°	Dip 45°-90°	Dip 20°-45°	Dip 0°-20°
Very unfavorable	Unfavorable	Fair	Favorable	Very favorable	Favorable	Fair

The cavability index is defined as:

$$CI = \sum_{i=1}^{7} w_i \times \frac{P_i}{P_{\max}} \tag{6}$$

where

w_i is the weight of the *i*th parameter,

P_i is the rate of the *i*th parameter (0 to 4),

and P_{max} is the maximum rate of the *i*th parameter (it is 4 for all parameters with the exception of joint persistence that is 3).

The collected data related to training cases were used to determine the associated CI for each case based on Eq. (2). Table 5 lists the main caving span and calculated CI for training cases, while their scatter plots are depicted in Figure 4.

In order to investigate the relationship between the main caving span (L_m) and CI, the curve fitting approach was applied. For this purpose, several curves were fitted on the data, and their RMSE and R^2 were calculated as shown in Table 6.

Table 5. Calculated CI for train cases.

Mine/Panel	Main caving span (m)	CI
Parvadeh1/E0	10.45	74.5
GDK 10A Incline mine/3D2	78.1	30.5
GDK 10A Incline mine/No.14	53	45
GDK 10A Incline mine/3A	64.9	46.83
Moonidih/A4	26	61.67
Svea Nord/C6	36	46.75
Highveld Coalfield	36.8	58.25
Malta Colliery/No.1	30	59
CONSOL Central Appalachian/8-R	85.34	14.5

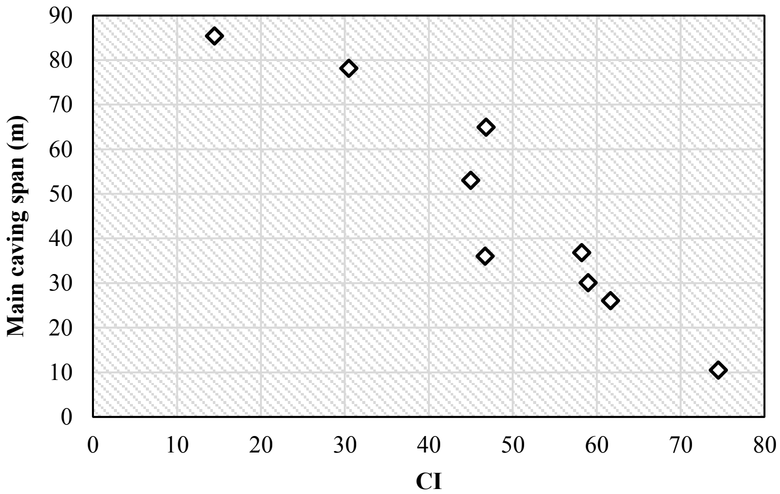


Figure 4. Scatter plot for main caving span *vs.* CI.

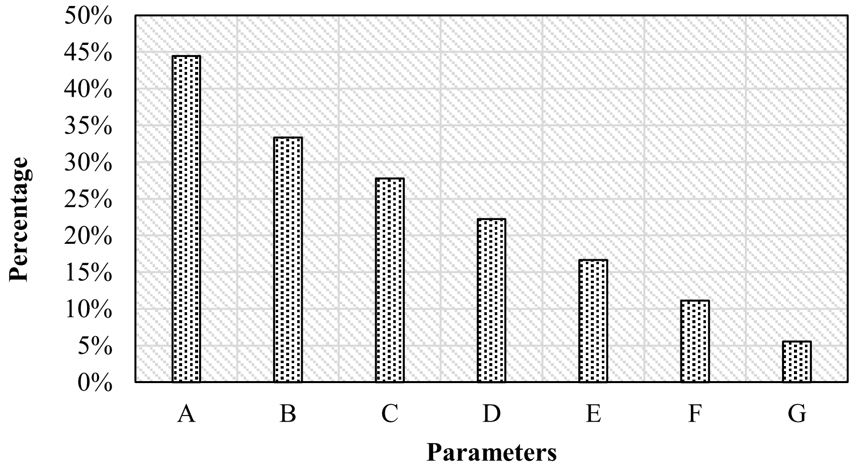
Table 6. Fitted curves and associated RMSE and R^2.

No.	Model	RMSE	R^2	Equation
1	Linear	9.51	0.87	$L_m = -1.41(CI) + 116.53$
2	Quadratic	9.03	0.89	$L_m = -0.012(CI)^2 - 0.34(CI) + 95.8$
3	Cubic	8.88	0.91	$L_m = 0.0006(CI)^3 - 0.097(CI)^2 + 3.04(CI) + 59.42$
4	Gaussian	8.44	0.90	$L_m = 86.88 \times e^{\frac{-(\mathrm{CI}-20.85)^2}{1406.62}}$
5	Exponential	12.96	0.75	$L_m = 135.91 \times e^{(-0.023(\mathrm{CI}))}$
6	Power	16.60	0.59	$L_m = 582.07(CI)^{-0.67}$
7	Logarithmic	12.38	0.73	$L_m = -48.18 \times \ln(CI) + 231.1$

It can be inferred from Table 6 that the Gaussian model has the lowest RMSE, whereas the cubic model has the highest R^2. Therefore, these models were selected as the candidate models, and their performances were evaluated in the validation cases.

3.2. Regression analysis

In this study, the independent variables were chosen based on the parameters frequency as reported in the literature. Accordingly, the percentage of each parameter usage in the previous empirical models was calculated, as shown in Figure 5.



***A**: Strata UCS; **B**: Strata thickness; **C**: RQD; **D**: Height of immediate roof, Coal seam thickness; **E**: Type of roof rock, Core data, Depth of coal seam; **F**: Height of main roof, Roof density, Tensile strength of main roof, Presence of groundwater; **G**: Miscellaneous parameters.*

Figure 5. Percentage of parameter usage in the literature.

It may be noted in Figure 5 that the strata uniaxial compressive strength, strata thickness, roof RQD, height of immediate roof, and coal seam thickness have had percentages more than 20% in the previous studies. Therefore, these parameters were considered as the input variables in the regression analysis with the exception of RQD because it was not available for all cases. In addition, the strata UCS and thickness were defined in terms of the equivalent immediate roof strength (EIRS), as in Eq. (1).

3.2.1. Linear regression model

In a multivariate linear regression model, the output is modeled as a function of independent variables. The data for 9 panels (out of a total of 12 collected panels) were applied to develop a linear regression model based on Table 1. Five tests were executed to validate the proposed linear regression function. The developed linear model for the main caving span is as follows:

$$L_m = 32.07 + 0.32(EIRS) - 3.16(h_i) + 9.71(t_{coal}) \tag{7}$$

where L_m is the main caving span, and h_i and t_{coal} are the height of immediate roof and the coal seam thickness, respectively.

3.2.2. Non-linear regression model

The twin-logarithmic model was incorporated to develop a non-linear multivariate regression relationship. The equation representing this relationship is as follows:

$$Y = aX_1^{b_1} \times X_2^{b_2} \times ... \times X_n^{b_n} \tag{8}$$

where Y is the dependent variable (output); a is the intercept; X_1, X_2, and X_n are the independent variables; and b_1, b_2, and b_n are the regression coefficients of X_1, X_2, and X_n, respectively.
Taking logarithms of both sides of Eq. (4):

$$\log Y = \log a + b_1 \log X_1 + b_2 \log X_2 + ... + b_n \log X_n \tag{9}$$

Eq. (5) can be rearranged as a linear regression function as:

$$Y^* = c + a_1 X_1^* + a_2 X_2^* + ... + a_n X_n^* \tag{10}$$

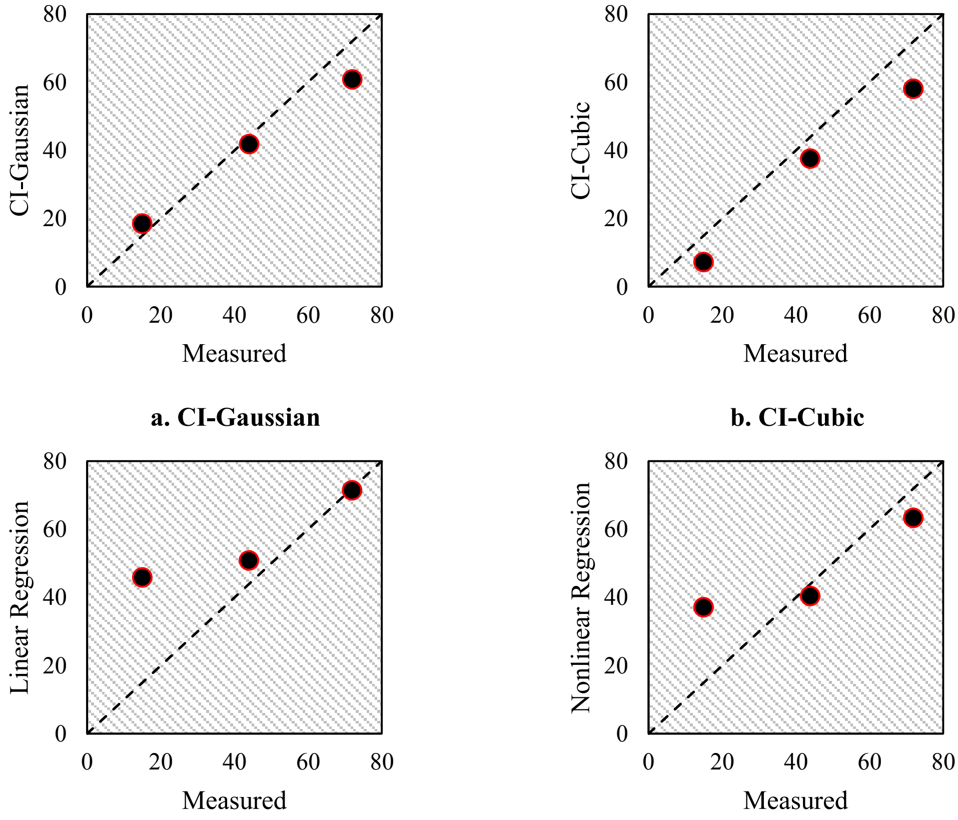
The regression analysis was performed, and five validation tests were carried out, following the previously-stated logic. The non-linear multivariate regression function that can be used to predict the span of the main fall was obtained, as shown in the following equation:

$$L_m = \frac{13.18 \times EIRS^{0.41} \times t_{coal}^{0.97}}{h_i^{0.63}} \tag{11}$$

4. Results

Capabilities of the four proposed models (CI in the Gaussian form, CI in the cubic form, and linear and non-linear regressions) were evaluated using three cases based on Table 1. In order to investigate the capabilities of the proposed models, the scatter graphs of the measured and predicted values were plotted. Ideally, on such a graph, the points are scattered around the 1:1 diagonal straight line. A point lying on the line indicates an exact estimation. A larger deviation from this line shows the larger errors in the prediction. The scatter graph for each model is depicted in Figure 6.

A comparison between the measured and predicted main caving span values is shown in Figure 7.



a. CI-Gaussian

b. CI-Cubic

c. Linear Regression

d. Nonlinear Regression

Figure 6. Scatter graph of measured main caving span versus predicted values using developed models.

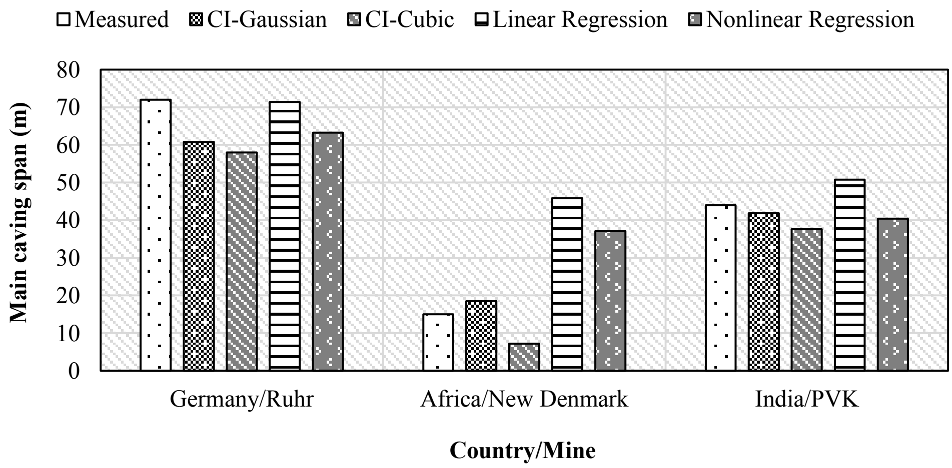


Figure 7. Comparison between measured and predicted span values.

Four criteria (R^2, RMSE, VAF, and MAPE), as mentioned in the Section 2, were used for the sake of quantitative comparison. Smaller RMSE values produce higher coefficients of determination, leading to more accurate fitted curves. In the same direction, higher VAF values and smaller MPAE values are desired for fitted relationships. The calculated values of these indices for the proposed models are given in Table 7.

According to the visual comparison (Figures 6 and 7) and performance criteria, it could be deduced that the CI models were capable of predicting the main caving span with a reasonable accuracy. In addition, the Gaussian model performed a higher accuracy when compared to that of the cubic model.

Table 7. Calculated performance criteria for proposed models.

Models	R^2	RMSE	VAF	MAPE
CI-Gaussian	0.9976	6.88	93.25	14.59
CI-Cubic	0.9895	9.97	98.00	28.71
Linear regression	0.8828	18.23	66.77	73.95
Nonlinear regression	0.8354	13.86	66.47	55.82

5. Discussion

The performance of each model was determined in the previous section. This section provides detailed discussion on the results.

The reason for the difference in the prediction results for the CI models and the regression is related to the parameters involved in each model. There are effective parameters such as roof discontinuities and ground water flow that cannot be considered in a regression model.

The roof strength of coal mines is influenced by the bedding plane or other discontinuities that weakens the rock structure. Furthermore, the stratified roof strata are cross-cut by sub-vertical joints that are either original or mining-induced. Therefore, the presence of these geological factors reduce the strength of the roof layer rock mass. Disregarding these features leads to an inaccurate prediction. For instance, in the studied panel of New Denmark colliery in Africa [24], the roof has some discontinuities such as joint set and bedding plane. Performance of the regression models in this panel highlights the importance of considering such properties. In contrast, incorporating RQD increases the accuracy of these models. Nevertheless, one may note that RQD is an index for fracture spacing, and the other discontinuity properties are not taken into account through it.

On the other hand, groundwater movement through rock mass redistributes stresses around joints and discontinuities within the rock mass. This reduces the normal stresses across the fractures lowering the shear strength of the joints based on the effective stress concept, confining that stresses across a joint or a bedding plane may be low in the proximity of excavations. In such cases, the movement of groundwater may lead to a large dilation of the joints/bedding planes, resulting in large inflows of water and instability of strata.

In addition, when a relationship is developed based on a database, the logical relationship between the output variable and the input variables may not be met. The relationships 3 and 7 show direct relations between the main caving span and the coal seam thickness, while in reality and based on the analytical model, this relationship should be inverse. This shows that the reliability of a data-based model is largely dependent on the size, quality, and consistency of the database. This is another disadvantage of the data-based methods.

An effective solution for considering all the effective parameters in a model to predict the main caving span is to develop a classification system, and consequently, an index. Also the level of significance for each parameter is required to be determined using the scientific methods. Finally, using the best-fitted curves on the actual data would result in the development of a reliable model. The results obtained confirm this solution.

6. Conclusions

Two methods were proposed for the prediction of the main caving span. Cavability index (CI) using the hybrid fuzzy MCDM and two relations using the regression analysis were developed. The following main conclusions could be drawn from this investigation:

- The Gaussian model, which defines the relationship between CI and the main caving span, was found to be superior in comparison with the other models with the coefficient of determination (R^2) and root mean squared error (RMSE) values of 0.9976 and 6.88, respectively.

- CI is a suitable approach to predict the main caving span in longwall projects due to the consideration of various types of effective parameters on the caving.

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تخمین دهانه تخریب اصلی در استخراج جبهه کار طولانی با استفاده از رویکردهای تصمیم‌گیری چند معیاره و آماری

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چکیده:

تخریب سقف بلاواسطه در روش استخراجی جبهه کار طولانی فرآیند دینامیکی پیچیده‌ای است که هسته مرکزی بسیاری از چالش‌ها و مسائل مرتبط با کنترل زمین و لایه‌ها محسوب می‌شود. از این رو، تخمینی قابل اتکا از رفتار لایه‌ها و پتانسیل تخریبی آن‌ها در مرحله طراحی پروژه‌های جبهه کار طولانی امری الزامی است. در این روش دهانه تخریب اصلی معیار کمّی نشان‌دهنده قابلیت تخریب لایه‌ها است. در این پژوهش، به منظور تخمین دهانه تخریب اصلی در پروژه‌های استخراجی با روش جبهه کار طولانی دو رویکرد متفاوت ارائه شده است. برای این منظور، در رویکرد اول شاخص قابلیت تخریب (CI) بر اساس یک روش ترکیبی تصمیم‌گیری چند معیاره با ترکیب دو روش تحلیل شبکه‌ای فازی و روش آزمایشگاه ارزیابی و آزمون تصمیم‌گیری فازی معرفی شده است. سپس رابطه بین شاخص قابلیت تخریب و دهانه تخریب اصلی تعیین شده است. در رویکرد دوم روابط آماری با استفاده از روش‌های رگرسیونی چند متغیره توسعه یافته است. به منظور توسعه این مدل‌ها از اطلاعات نه پهنه استخراج شده استفاده شده است. بر این اساس دو مدل مبتنی بر CI شامل مدل گوسینی و مدل تابع درجه سه و همچنین مدل‌های رگرسیونی چند متغیره خطی و غیرخطی پیشنهاد شده‌اند. در انتها عملکرد مدل‌های توسعه یافته با استفاده از داده‌های پهنه‌های مختلفی مورد بررسی قرار گرفته است. نتایج به دست آمده نشان می‌دهد که مدل گوسینی مبتنی بر CI در تخمین دهانه تخریب اصلی دارای عملکرد بهتری نسبت به دیگر مدل‌ها بوده است. این نتایج مؤید این نکته است که عدم توانایی مدل‌های رگرسیونی تجربی در دخیل کردن تمام پارامترهای مؤثر موجب ایجاد خطای زیاد در عملکرد آن‌ها می‌شود.

کلمات کلیدی: دهانه تخریب اصلی، شاخص قابلیت تخریب، استخراج جبهه کار طولانی، تصمیم‌گیری چند معیاره، تحلیل رگرسیونی.