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Stochastic modelling of Continuous Miner based underground coal mine production planning through curve-fitting and regression approach

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Abstract
In India, three major and effective technologies for underground coal mining are continuous miners (CM), shortwalls, and longwalls. According to the relevant literature, the available studies have not been able to successfully link the productivity of CM-based systems to the related independent parameters. However, this study makes an effort to find correlations between a number of independent variables and production-related attributes using regression modelling and curve fitting. A combined relationship was constructed considering all independent parameters as input and production-related parameter as output, and a relationship was made considering each input parameter separately with the production-related parameter as output. The idea of their strong association to represent the interrelationship conveyed by their statistical goodness of fit (R^2 and RMSE) and the results of the t-test further support their relevance. The greatest R^2 value was shown for seam thickness (0.8779), followed by pillar area (0.84), gradient (0.8112), and coal strength (0.6008). Besides geo-mining input parameters, the cutter motor power has shown a better correlation with production-related parameter, with its corresponding R^2 values of 0.8033. The pertinent data from three CM panels (not considered during equations generation) were then incorporated into the derived interrelationships. These validation results were then compared using a t-test to the equivalent actual field data, which revealed a minor discrepancy. The interrelationships were found to be applicable and pertinent in CM–based underground coal mining situations.

Keywords
Underground coal mining, goodness of fit test, model validation, Root Mean Square Error (RMSE), Uniaxial Compressive Strength (UCS)

Introduction

One of India's main mining endeavours is coal production, significantly contributing to the nation's revenue generation. In the Indian context, opencast mining is the main coal-winning technology. The global trend, however, is different; it favours mass-production technologies for underground coal mining, which have substantially less environmental impact than opencast mining methods. It is also important to note that conventional room and pillar mining has a lower productivity rate, accounting for most underground coal mining in India. The government has now taken the initiative to implement modern underground coal mining techniques, which have been popular for decades in other significant coal-producing countries. These effective technologies include Longwall mining and Continuous mining. The Single or Double-Ended Ranging Drums (SERD/DERD) found on Longwall machines are ideal for exploring long and regular coal blocks. However, the Continuous Miner (CM) machine works well with the common room and pillar method of mining and thus is compatible with both new and old panels during the development and depillaring, making it the most appropriate equipment for the underground coal mining scenario in India.

On the CM systems, some work has previously been done in the areas of performance inquiry, overall equipment effectiveness (OEE) analysis, and system reliability analysis. This paper indicates some relevant literature corresponding to CM systems as well as other mining systems, the applicability of statistical tools, parameters, and techniques, and various numerical modelling phenomena. In addition to this, a few works of literature related to challenges in mining, including human factor parameters, are also discussed.

Logistic regression based model to predict the severity of roof fall accident was prepared by Palei & Das (2009), coal cuttability modelling with relevant input parameters was presented by Singh et al. (1995), roof convergence modelling using multivariate regression was accomplished by Mandal et al. (2018), factors influencing work related injuries for miners were identified using multivariate regression by Paul (2009), interrelation between coal production and safety parameters were identified by Feng & Chen (2013), stochastic modelling of Gob Gas Venthole (GGV) was presented by Karacan & Luxbacher (2010), Gao et el. (2021) analysed the combined effects of multiple parameters on spontaneous heating of coal, modelling the phenomenon of energy generation using organic solid waste was proposed by Ramesh et al. (2016), effects of gas outburst on underground coal mining was modelled using logistic regression by Li et al. (2015), Abdulredha et al. (2018) modelled the interrelationship between Municipal Solid Waste (MSW) production and hotel features using multivariate regression, Dahal & Routray (2011) studied the effects of soil parameters on crop yield through multivariate regression modelling, mine worker characteristics and severity of injury was modelled using multiple regression by Hull et al. (2015), the interrelationship between primary energy consumption and greenhouse gas emission was modelled by Wiecek (2015) through multiple regression, Tyulenev et al. (2017) focused on the productivity of hydraulic backhoe in Russian open pit coal mine considering the layer thickness and loading position of dump truck as important parameters, Blistanova et al. (2016) focused on preparing a flood vulnerability model using Multiple Criterial Analysis (MCA) and Geographical Information System (GIS) tools in the Bodva river basin of eastern Slovakia.

The utility of the hybrid modelling approach and its advantages over the conventional modelling techniques were described by Guo et al. (2021). A formula for calculating the capital cost required to establish a coal mine was proposed by Mohutsiwa & Musingwini (2015) through a parametric modelling approach. Kim et al. (2006) produced a hazard map for abandoned coal mines in Korea using combinations of probabilistic model, logistic regression and Geographic Information System (GIS), Que et al. (2016) proposed a simulated optimisation technique for efficiency improvement of the continuous transportation system for oil and sand through Ground Water Articulating Pipeline (GWAP), Islavath & Bodakunta (2022) worked on identification of optimised pillar extraction techniques numerically for CM working, Bartoš et al., (2014) presented an overview of open source photogrammetric software and their benefits over the subscription-based packages.

Reliability analysis through a graphical approach for sub-systems of CM was presented by Banerjee (2017), OEE to represent the effectiveness of two CM systems deployed in two underground coal mines in India was represented by Banerjee (2019), the OEE of a CM system was evaluated, and further Failure Modes and Effects Analysis and reliability analysis was performed on that CM system; further vulnerable sub-systems and their significant failure modes were identified by Banerjee & Dey (2022).

Carpick et al. (1999) presented a general introduction to curve-fitting applications by modelling a complex phenomenon. Nevertheless, the characterising parameters of a good curve-fitting for a forecasting model of the fossil fuel industry were represented by Wang & Feng (2016). Alvarez et al. (2021) presented a MATLAB-based simulation approach for the steam generator. A new strategy to develop a River Water Quality Model (RWQM) using a small data set was explained by Cui et al. (2019). Achanti & Khair (2001) investigated the effects of four independent parameters on the bit geometry of a cutting machine using a graphical modelling technique. Zhang et al. (2021) described the ore production details and recovery rate data for twenty-five minerals and finally calculated the losses of twenty minerals between 1920-2018. Simionescu et al. (2022) evaluated the effects of governance on controlling pollution by mandating the use of renewable energy in ten European countries using the autoregressive distributed lag (ARDL) model. Cehlár et al. (2017) presented a case study to assess the impacts of gold mining and processing in the Slovak Republic.

Ranjith et al. (2017) stated that the technical and challenging environment of deep mining becomes significant where innovative solutions are needed as additional safety measures. Kholod et al. (2020) proposed a novel methodology involving methane emissions strategy from abandoned mines. The experimental results established a faster increase in abandoned mines with respect to methane emissions than in active mines. Kazanin et al. (2021) stressed OSH management, including environmental factors that make the products qualitative and competitive. As mining operations are becoming more intensive and the average depth of mining is growing so, there is a significant chance of an increase in methane emission and associated risks. Selyukov et al. (2020) proposed the limitation of the continuous lateral mining method, where the final quarry depth is determined by the vertical height of the underground mine working floor. Dyczko et al. (2020) remarked on the advantages and disadvantages of using shearer and plough systems where the impact on the quality of ROM (Run of Mine) minerals is analysed. Sánchez & Hartlieb (2020) discussed the importance of innovation in the mining industry, where a review of drivers and actors is described from the perspective of current trends. Dey & Sharma (2013) focused on the application of ergonomics to control the impact of the underground environment on the mine operators' health. Dey et al. (2018) stated the fatigue and musculoskeletal disorder (MSD) related problems of continuous mining operators under a given mining environment. Sharma et al. (2016) studied the development of cardiac and postural strain of Side Discharge Loader (SDL) operators under a hostile underground mine environment.

A thorough review of available literature in the field revealed a few facts, such as – previous studies did not warrant adequate attempts to link the variables affecting productivity and overall performance for a CM-based underground coal mining system. Besides this, it was also observed that curve-fitting and regression are two effective tools for stochastic modelling of any system. In the present study, an effort was made to apply regression modelling and curve-fitting to correlate the input-output phenomenon of a CM-based underground mine operation system and further validate the model in connection with its practical implementation. This research work may bridge the gap for a predictive tool for equipment selection during a machine's operational phase and pre-commissioning stage, thereby improving equipment usage, effectiveness, and system productivity.

Methodology

From the significant literature survey, the methodology for this research work has been decided, which has been schematically presented in Fig.1.

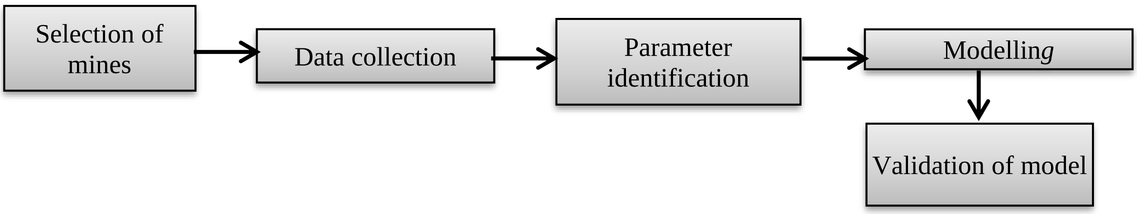


Fig.1. *Flowchart of methodology*

The study starts with a selection of suitable mines that have deployed CM machines for coal production underground. Field visits were carried out for a considerable period in each CM panel to collect relevant information related to the study; this includes the daily production from machine, machine specification and geo-mining condition-related information. Subsequently, the relevant parameters for model development were identified and discussed with experienced mine personnel, and a research project was sought based on these parameters. Further, interrelationship models were developed using MATLAB R2021a with the data sets from eleven CM panels considered for study. Whereas data sets corresponding to three CM panels were kept aside for validation purposes using the XLSTAT add-in of MS-Excel.

The interrelationship development is based on the concept of determining relationships by considering the production-related parameter as output and geo-mining and machine parameters as input. Nevertheless, the interrelationships between one input and output for each input parameter were identified, in addition to a combined effect relationship model (where all input parameters were considered together as input and production-related parameter was considered as output). The one input-output equations (interrelationships) were identified by the curve-fitting application of MATLAB R2021a, whereas the multiple input and one output equation was identified using multiple regression application of XLSTAT add-in of MS- Excel. Subsequently, these equations were modelled using Python programming for ease of operation and model validation. Finally, the developed models were validated using data from three CM panels, which were not considered for equation generation.

Description of input parameters

The performance of a production system depends on several factors. However, in this case, the factors that were considered for modelling may be divided into two categories: parameters related to geo-mining conditions and parameters related to machines. However, the performance of the CM-based production system is affected by many additional parameters, such as environmental factors, inventory management, worker productivity, socio-physical factors, operational aspects, and many more. Conversely, these parameters do not significantly affect production performance, so the critical parameters within the group of geo-mining and machine specifications as identified by skilled mine personnel and engineers were considered for model development; these are namely- seam thickness, gradient, pillar area, coal strength, cutter drum width, cutter drum diameter, cutter rpm and cutter motor power. The basic summary of these parameters and their mode of effect on the productivity of underground mines are described below:

Seam thickness:

It indicates the availability of extractable coal in a seam. Low seam thickness results in poor coal production from a single pass of cutting. Conversely, an extremity of seam thickness also does not result in optimum utilisation. Modi et al. (2017) identify that a seam thickness of 3.5 to 6 m is optimum.

Gradient:

Seam gradient drastically affects the efficiency of transport machines (shuttle car or ram car); a higher gradient increases transport cycle time. It has been reported by Modi et al. (2017) that a gradient not steeper than 1 in 10 is optimum for working with a CM machine.

Pillar size:

The pillars are the load-bearing members of the overburden strata. Extremely large pillar size results in ventilation problems besides delaying the transportation system, whereas smaller pillar sizes result in frequent movement of the CM machines between the working faces. Modi et al. (2017) indicate that pillar size within the range of 20 m – 30 m (centre to centre) is optimum for the operation of CM.

Coal strength:

The strength of coal is an important factor for panel design and speculating the life of cutting picks. Singh et al. (1995) indicate that selecting proper picks is important based on the Uni-axial Compressive Strength (UCS) of coal. In general, the UCS of coal ranges from 12 to 25 MPa. However, sudden impact with a harder stone is a major reason for pick breakage in practical mining scenarios.

Cutter diameter:

This is the diameter of the cutting drum on which the picks are mounted. For the standard height CM machines, the diameter of the cutter ranges from approximately 0.95 m to 1.1 m.

Cutter width:

This is the dimension of the cutter in the transverse direction. Generally, a standard height CM machine requires two passes to extract coal from the entire gallery width (approximately 6 m) as they are equipped with a cutter ranging between 3 to 3.5 m. Nonetheless, besides causing maneuverability problems, extremely wide cutters result in higher coal production during the first pass and a lack of remainder coal in the second pass. On the other hand, a very small cutter width increases the number of cutting passes. Therefore, the selection of optimum cutter width is of prime importance.

Cutter motor power and cuter rpm:

These are basically two different parameters considered in the course of this study. However, the cutter motor power indicates the motor's ability to overcome unwanted obstacles, thus reducing the chance of jamming.

Whereas the cutter rpm is the number of revolutions the cutter makes per minute, Zhao & Liu (2019) correlate this to a CM machine's cutting and loading rate. Therefore, it is considered an important parameter for the production modelling through CM machine.

A descriptive picture of a continuous Miner machine is depicted below (Fig.2).

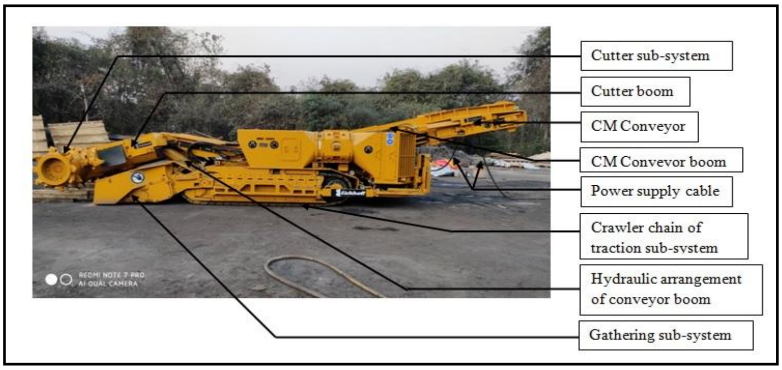


Fig.2. *Continuous Miner machine and its sub-systems*

Description of the mines under study

In this research, CM projects from every corner of the nation are included, with a focus on West Bengal, Chhattisgarh, Madhya Pradesh, and Telangana. Data corresponding to eleven panels (Mines A to Mines I, where Mine-A and Mine-I have deployed two CM machines each in different panels) were used for interrelationship development, while data of the other three projects (Mine-J, Mine-K, Mine-L) were reserved for validation purposes only.

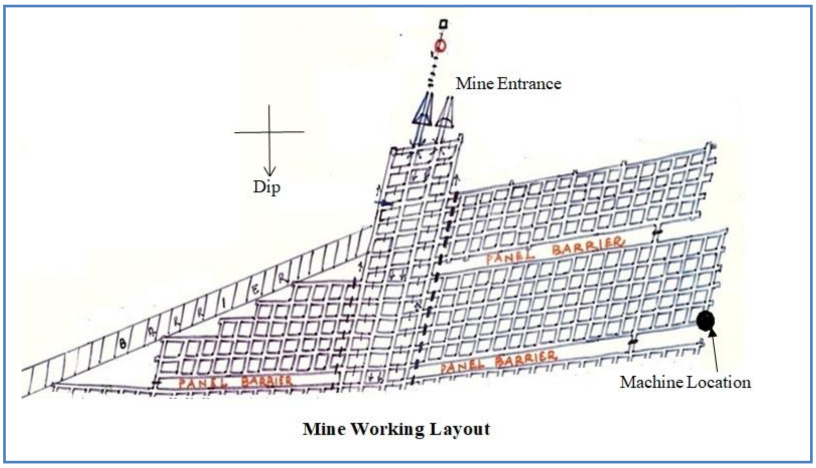


Fig.3. *Working layout of one CM panel*

One of the eleven CM panels is shown above, where geo-mining parameters, as listed in Table 1 below, have been used as input parameters for model development. The CM machine's working location has been marked as a dark black round label within the panel (Fig. 3). The exact location of the machine is at the 18th dip of the 11th level. One more such CM was deputed in the succeeding panel. Each CM machine has shuttle cars and a feeder breaker to make a complete composite system. Every CM machine has its predetermined target of coal production, where the cutting rate, including the transportation of coal, seems to be an important factor.

Tab.1. Geo-mining parameters of 11 CM panels considered for equation formation

Name of mine	Seam thickness (m)	Gradient	Pillar size (m × m)	Gallery width (m)	Uniaxial Compressive Strength of coal (MPa)	Pillar area (m^2)
Mine-A (Panel-1)	4.5	1 in 16	32 × 32	6	22.22	676
Mine-A (Panel-2)	4.5	1 in 16	32 × 32	6	29.11	676
Mine-B	4.75	1 in 15	34 × 34	6	12.72	784
Mine-C	3.8	1 in 90	35 × 35	6	16.44	841
Mine-D	3.5	1 in 17	20 × 20	6	26.52	196
Mine-E	5.05	1 in 16	36 × 36	6	19.77	900
Mine-F	5.92	1 in 17	32 × 32	6	28.35	676
Mine-G	7	1 in 4 (1 in 7.5 apparent dip)	75.5 × 65.5	5.5	23.2	4200
Mine-H	6.5	1 in 7.5	45 × 45	6.5	30.02	1482
Mine-I (Panel-1)	4	1 in 18	45 × 41	6	17.85	1365
Mine-I (Panel-2)	4	1 in 18	54 × 56	6	29.17	2400

Model development

The model development is based on a few assumptions, as stated below:

- Only standard-height CM machines were considered for the study.
- Environmental factors such as temperature, pressure, and relative humidity were considered uniform during the course of this study.
- The absenteeism of employees, psychological and physiological factors has a minor impact on productivity.
- The cycle times of all the shuttle cars are considered the same for all the panels.
- Investigation revealed that the supply chain management was well-planned and adequately managed.
- Fault detection, replacement and repair of any sub-system have negligible impact on productivity.

Nomenclature of input parameters:

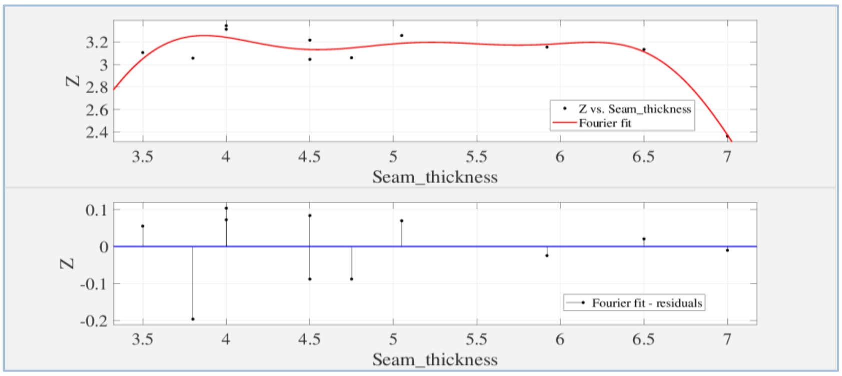
Here, the geo-mining parameters and machine parameters were considered input parameters, namely seam thickness, gradient, pillar area, coal strength, cutter motor power, cutter diameter, cutter width, and cutter rpm. Descriptive details of these input parameters have been mentioned in the "description of input parameters" section of this paper. The output parameter considered in this case is the logarithmically transformed values of the average daily coal production (Z) for each mine. This logarithmic transformation was performed to better fit the curve and develop accurate interrelationships. The nomenclature of the input and output parameters are as follows-

X_1 = Seam thickness in m
X_2 = Gradient in degree
X_3 = Pillar area in m^2
X_4 = Coal strength or Uni-axial Compressive Strength in MPa
X_5 = Drum width in m
X_6 = Drum diameter in m
X_7 = Cutter motor power in kW
X_8 = Cutter rpm
Y = Average daily coal production (in tonne) for a corresponding period for each mine
$Z = log_{10} Y$

Identification of interrelationships:

Here, an effort was made to identify the interrelationship between each input parameter and the output parameter (Z). In addition, a combined effect relationship model was developed using a multiple regression method where all the input parameters (X_1 to X_8) were considered input and Z was considered output. Eleven CM panels were considered for the analysis; which yielded eleven values against each input and output parameter. It is worth mentioning here that the geo-mining parameters corresponding to Mine-G were not standard, and the mine had various kinds of abnormalities in general working conditions for a standard height CM machine. Therefore, the input and output relationships deviated largely from the regular range.

The curve-fitting plots, along with their governing equations for each input parameter against the output (Z), are described as follows:



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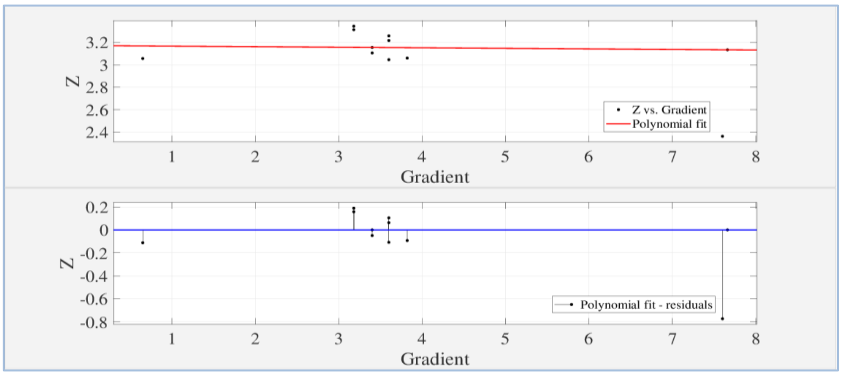

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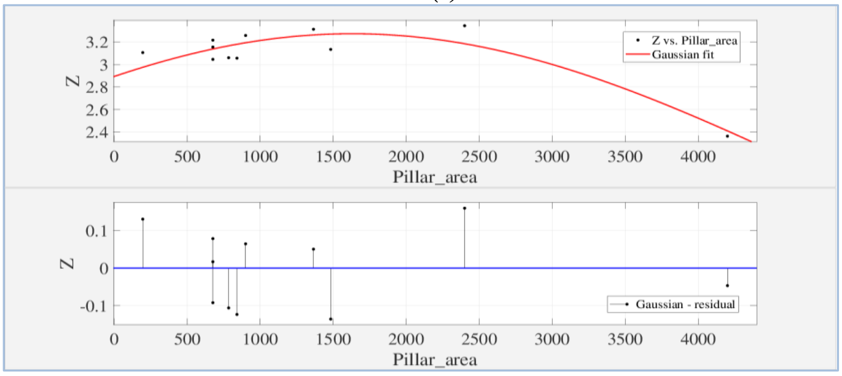

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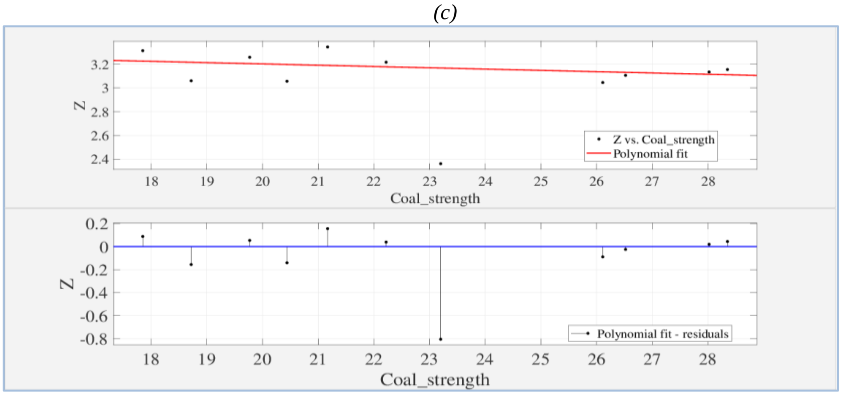


(d)

Fig.4. *Curve-fitting and residual plots between a. seam thickness and Z, b. gradient and Z, c. pillar area and Z, d. coal strength and Z*

The above Fig. 4 depicts the curve-fitting plot (upper one) and residual plot (lower one) between each geo-mining parameter and Z. Curve-fitting plot between seam thickness and Z justifies the incompatibility of extreme seam thickness for working of the CM system (Fig. 4a) besides that the residual plot depicts a minimum deflection; thus, substantiating the goodness of fit of the curve-fitting plot. The governing equation corresponding to the plot depicted in Fig.4.a. is mentioned as follows (Eq. 1).

$$log_{10} Y = 2.668 + 0.8175\, cos(X_1 \times 1.171) - 0.3062\, sin(X_1 \times 1.171) - 0.4044\, cos(2 \times X_1 \times 1.171) + 0.3409\, sin(2 \times X_1 \times 1.171) + 0.1132\, cos(3 \times X_1 \times 1.171) - 0.1417\, sin(3 \times X_1 \times 1.171) \quad (1)$$

The curve-fitting plot between gradient and Z (Fig. 4b) depicts a gradually decreasing trend of Z with an increase in gradient; this is quite natural as the efficiency of the transport machinery gets drastically reduced with increased gradient. The residual plots also confirm a good fit, which was further substantiated statistically. The governing equation of the curve-fitting plot depicted in Fig. 4b is mentioned hereunder (Eq. 2).

$$log_{10} Y = (-0.009795 \times X_2) + 3.153 \quad (2)$$

Fig. 4c depicts the curve-fitting and residual plot, where the pillar area is considered as input and Z is the output. Corresponding curve-fitting shows that a pillar area within the range of 1000 m^2 to 2000 m^2 gives the highest output; it also depicts that the extremity of the pillar area negatively affects productivity. The residual plot also depicts minor variations from the recorded values of Z, thus indicating a good fit of the curve. The corresponding equation representing the curve (Fig. 4c) is mentioned here as Eq. 3.

$$log_{10} Y = 3.274 \times e^{-[(\frac{X_3 - 1631}{4636})^2]} \tag{3}$$

Fig.4.d. shows the residual and curve-fitting plot between coal strength and Z. The curve shows a steady decline in Z with increased coal strength, which is perfectly valid because greater strength also increases the resistance the coal offers. A condition with a good fit is also shown in the residual plot. Eq. 4 is the governing equation for the curve seen in Fig. 4d above.

$$Z = log_{10} Y = -0.01094\, X_4 + 3.422 \tag{4}$$

Table 2 further shows the statistical goodness of fit results of the governing equations corresponding to the geo-mining parameters (Eq. 1 to Eq. 4).

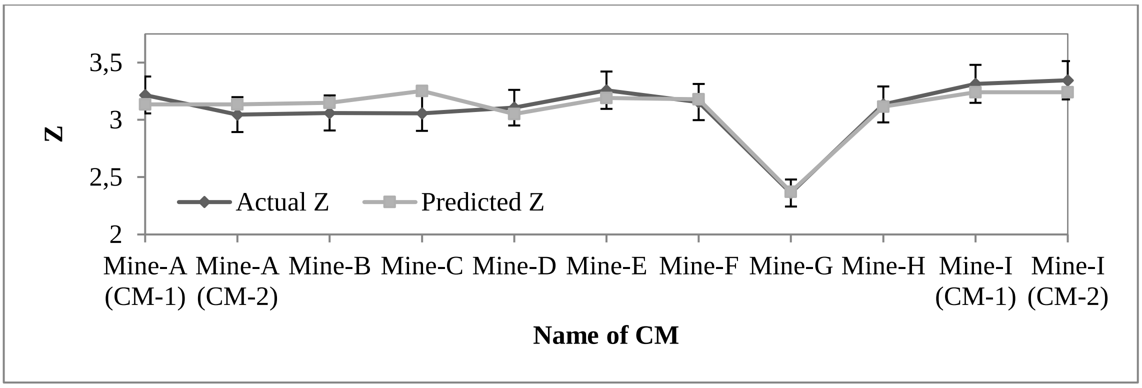
Tab.2. Statistical goodness of fit results for equations corresponding to geo-mining parameters.

Sl. No.	Equation Name and No.	The goodness of fit result	*t*-test result (α = 0.05)	Remarks
1.	Seam thickness and Z (Eq.1.)	R-square: 0.8779 Adjusted R-square: 0.5932 RMSE: 0.1689	*p*-value = 0.999	*p* > *a*; so the null hypothesis cannot be rejected
2.	Gradient and Z (Eq.2.)	R-square: 0.8121 Adjusted R-square: 0.7913 RMSE: 0.121	*p*-value = 0.538	*p* > *a*; so the null hypothesis cannot be rejected
3.	Pillar area and Z (Eq.3.)	R-square: 0.84 Adjusted R-square: 0.8 RMSE: 0.1184	*p*-value = 0.998	*p* > *a*; so the null hypothesis cannot be rejected
4.	Coal strength and Z (Eq.4.)	R-square: 0.6008 Adjusted R-square: 0.5565 RMSE: 0.1763	*p*-value = 0.366	*p* > *a*; so the null hypothesis cannot be rejected

Note:
For the above t-tests, the null (H_0) and alternate (H_a) hypothesis are as follows:
H_0 = The difference between the means is equal to 0.
H_a = The difference between the means is different from 0.

As mentioned in Table 2, the goodness of fit results delineate a good fit as their R^2 and adjusted R^2 values tend towards one, whereas the Root Mean Square Error (RMSE) value tends towards zero. From Eq. 1 to Eq. 4, the predicted value of Z is obtained easily by putting pertaining data to the equation. The further t-test between predicted and actual Z for all eleven CM panels considered for study has depicted no difference in their means for Eq.1 to Eq.4 (as for all equations $p > a$); thus, it substantiates the relevance of the equations 1 to 4.

Nevertheless, the aforementioned equations (Eq. 1 to Eq. 4) were fed with their respective input values recorded during field trips and compared with actual outputs (Z values) collected during those visits to validate the statistical goodness of fit test further. Here, a 5% error bar was used in the graphical comparison between the actual and predicted Z, as shown in Fig. 5a and Fig. 5b. The graphical validations for two geo-mining parameters are shown here; the other two, which likewise showed a similar trend with little fluctuation, are not shown.



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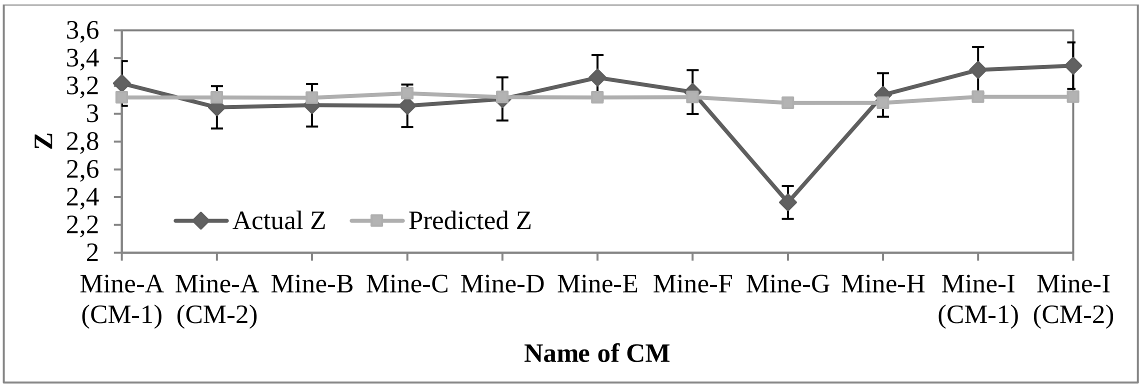
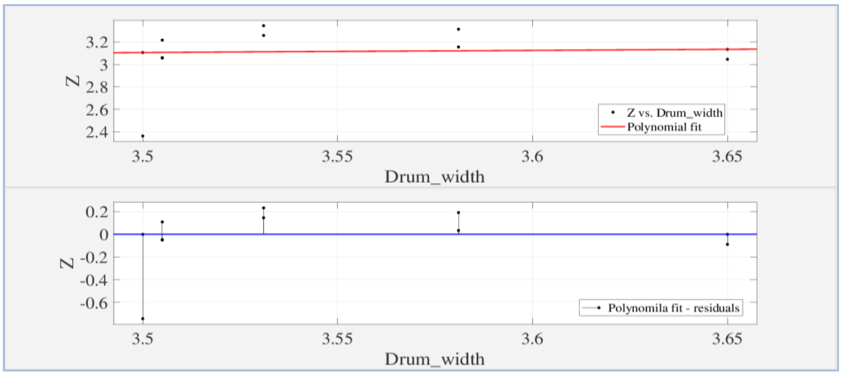


(b)

***Fig.5.** Comparison between actual and predicted output (Z) for a. seam thickness values, b. gradient values.*

The discrepancy between predicted Z and real Z are found to be within the 5% error bar from the aforementioned comparisons (Fig. 5a and 5b), which graphically supports the associated equations. However, the final validation results are further discussed in this paper.

Subsequently, the relationships between the machine parameters and the production-related parameter (Z) are established similarly. The following figures (Fig. 6a to 6d) show the associated curve-fitting and residual graphs.



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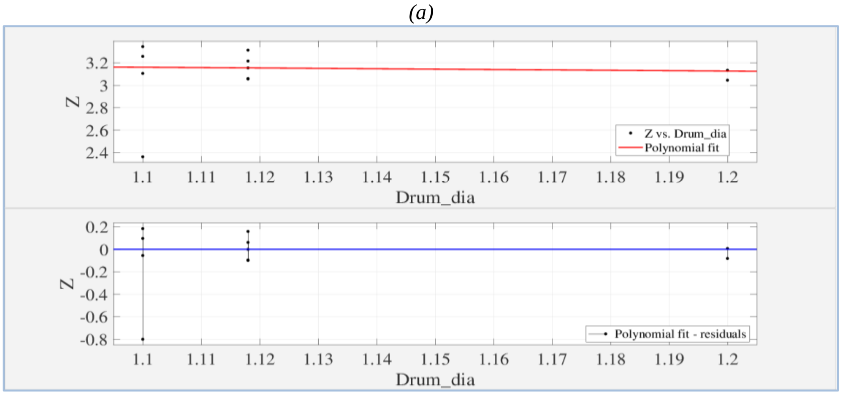

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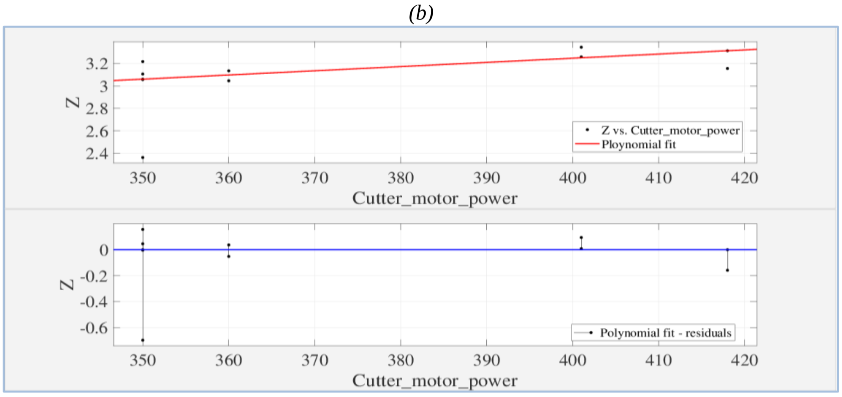

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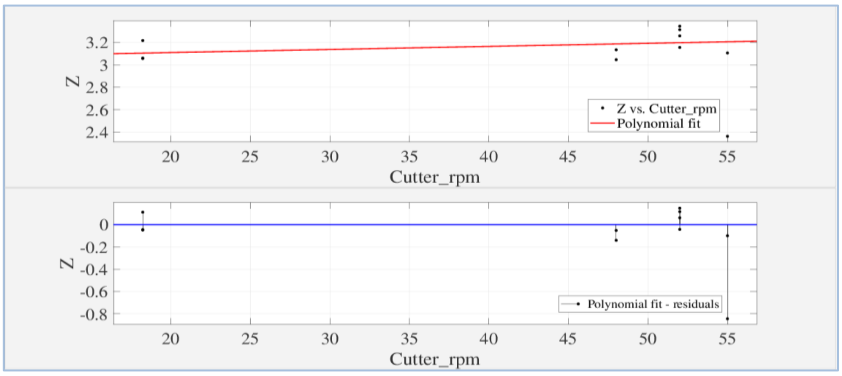


(d)

Fig.6. *Curve-fitting and residual plot between a. drum width and Z, b. drum diameter and Z, c. cutter motor power and Z, d. cutter rpm and Z*

The curve-fitting plot between drum width and Z is depicted in Fig. 6a along with its corresponding residual plot. The curve indicates a very slight rising tendency as the drum width increases, and residual plots describe minor deflections of the curve with actual values. Statistical goodness of fit for the above curve-fitting is mentioned in the following Table 3, and its corresponding governing equation is mentioned below (Eq. 5).

$$log_{10} Y = (0.01095 \times X_5) + 3.116 \quad (5)$$

Fig. 6b shows the curve-fitting and residual plot between drum diameter and Z, where it can be seen that the drum diameter affects the output very minutely, as it shows a minor reduction in output with increased drum diameter. The residual plot shows a minor deflection for most of the cases. The governing equation for the corresponding fitted curve is mentioned below as Eq. 6. Further goodness of fit test results for the curve-fitting are depicted in the following Table 3.

$$log_{10} Y = (-0.3435 \times X_6) + 3.54 \quad (6)$$

The curve-fitting and corresponding residual plot between cutter motor power and Z is depicted in Fig. 6c. Where it can be seen that the value of Z gradually increases with an increase in cutter motor power, and the residual plot also depicts minor deflection from the actual values. The governing equation for the corresponding curve (Fig.6.c.) is mentioned as Eq. 7, whereas the statistical goodness of fit results are mentioned in table-3.

$$log_{10} Y = (0.003732 \times X_7) + 1.754 \quad (7)$$

Curve-fitting and residual plots corresponding to cutter rpm and Z depict an increasing production trend with an increase in cutter rpm (Fig. 6d); the corresponding residual plot depicts a minor deflection. The governing equation related to the curve is mentioned in the following Equation 8. Further, the statistical goodness of fit for this curve-fitting is mentioned in Table 3.

$$log_{10} Y = (0.002737 \times X_8) + 3.056 \quad (8)$$

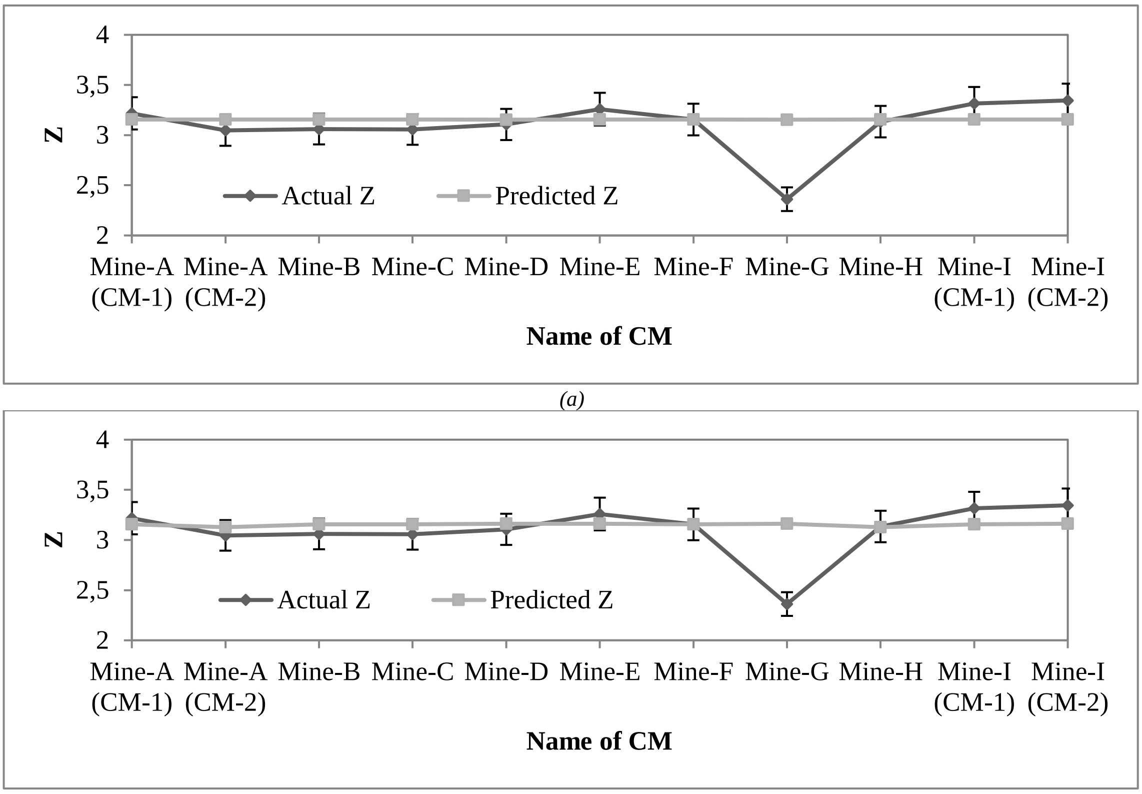
Tab.3. Statistical goodness of fit results for equations corresponding to machine parameters

Sl. No.	Equation Name and No.	The goodness of fit result	*t*-test result (α = 0.05)	Remarks
1.	Drum width and Z (Eq.5.)	R-square: 0.7462 Adjusted R-square: 0.718 RMSE: 0.1406	*p*-value= 0.472	$p > a$; so the null hypothesis cannot be rejected
2.	Drum diameter and Z (Eq.6.)	R-square: 0.7339 Adjusted R-square: 0.7044 RMSE: 0.144	*p*-value = 0.486	$p > a$; so the null hypothesis cannot be rejected
3.	Cutter motor power and Z (Eq.7.)	R-square: 0.8033 Adjusted R-square: 0.7815 RMSE: 0.1238	*p*-value = 0.558	$p > a$; so the null hypothesis cannot be rejected
4.	Cutter rpm and Z (Eq.8.)	R-square: 0.5991 Adjusted R-square: 0.5545 RMSE: 0.1767	*p*-value = 0.357	$p > a$; so the null hypothesis cannot be rejected

Note:
For the above *t*-tests, the null (H_0) and alternate (H_a) hypothesis are as follows:
H_0 = The difference between the means is equal to 0.
H_a = The difference between the means is different from 0.

The goodness of fit results shown in Table 3 above indicate a good fit because the R^2 and adjusted R^2 values tend to be one, while the Root Mean Square Error (RMSE) value tends to be zero. However, the results of the t-test on the predicted and actual Z as obtained from Eq. 5 to Eq. 8 for each of the eleven CM panels that were taken into consideration for the study showed no difference in their means (as for all equations $p > a$), which supports the relevance of those equations.

Subsequently, a graphical comparison between the actual Z values and the Z values obtained by feeding the corresponding inputs into their associated governing equations (predicted Z) was performed with a 5% error bar for additional validation. Small variations between actual and predicted Z values represent a better fit during the corresponding curve-fitting. The Graphical comparison plots are depicted in the following Fig. 7a and Fig. 7b. Here, the graphical validations for two machine parameters are depicted; however, the other two parameters also represented similar trends of minimal variation; therefore, they are not represented here.



(b)

Fig.7. *Comparison between predicted and actual Z value for a. drum width, b. drum diameter.*

From Fig. 7a and Fig.7b, it can be identified that the variation between actual Z and predicted Z is minimal (within a 5% error bar), which substantiates the relevance of the governing equation and provides better curve-fitting properties.

Further, the governing equation considering all input parameters (geo-mining and machine parameters) together as input and Z as output was obtained by multivariate regression using XLSTAT add-in of MS-Excel. The corresponding equation is mentioned in Eq. 9.

$$log_{10} Y = 36.55 - (0.2322 \times X_1) + (0.11421 \times X_2) - (0.000078 \times X_3) + (0.023075 \times X_4) - (23.428 \times X_5) + (35.016 \times X_6) + (0.028 \times X_7) + (0.000934 \times X_8) \quad (9)$$

The corresponding values of each input parameter, as recorded from each mine, were fed as input to the above-mentioned Eq. 9, which gave output values (predicted Z) corresponding to each mine. These output values were then graphically compared to the actual values of Z recorded during field visits to assess the equation's significance. This graphical comparison is shown in Fig. 8 below.

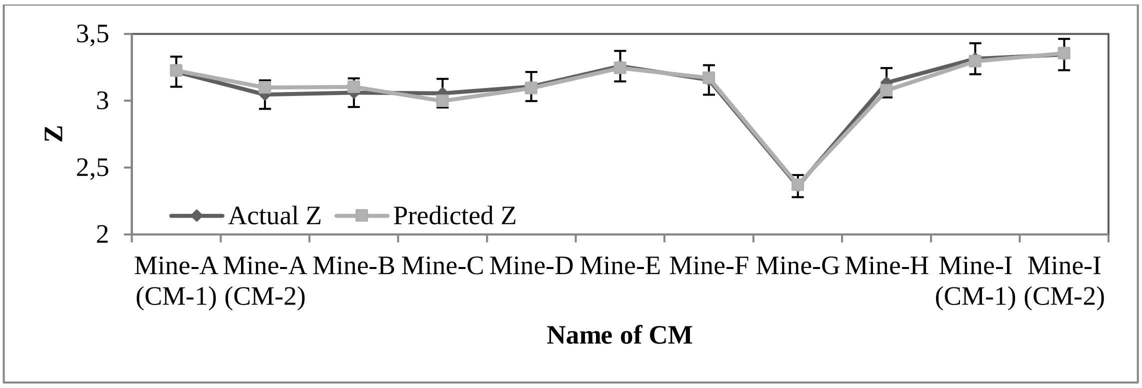


***Fig.8**. Comparison between actual and predicted output (Z) for the combined equation*

The variation between real Z and predicted Z is minor, as seen in Fig. 8, which indicates that the relevant equation has good prediction accuracy. Further, the results of the statistical *t*-test and goodness of fit are shown in Table 4 below.

Tab.4. Goodness of fit test results for combined effect relationship equation.

Sl. No.	Equation Name and No.	The goodness of fit result	*t*-test result ($a = 0.05$)	Remarks
1.	Combined effect relationship model (eq.9)	R square = 0.982 Adjusted R square = 0.911 RMSE = 0.079	*p*-value = 0.983	$p > a$; so the null hypothesis cannot be rejected

Note:
For the above *t*-test, the null (H_0) and alternate (H_a) hypothesis are as follows:
H_0 = The difference between the means is equal to 0.
H_a = The difference between the means is different from 0.

The information in Tables 2, 3, and 4 above shows that each equation's *p*-value and associated goodness of fit is significantly good, which supports the relevance of each equation's input and output properties. Therefore, field data corresponding to three CM projects not considered for equation creation were used to further validate all equations (Eq.1. to Eq.9).

Validation results

As already mentioned, the datasets corresponding to three CM projects (Mine-J, Mine-K and Mine-L) were considered to validate all equations mentioned in this paper. Table 5 represents the data corresponding to all input parameters (X_1 to X_8) that were used for the purpose.

Tab.5. Equation validation datasets

Mine Name	Seam Thickness (X_1)	Gradient (X_2)	Pillar area (X_3)	Coal strength (X_4)	Drum width (X_5)	Drum diameter (X_6)	Cutter motor power (X_7)	Cutter rpm (X_8)
Mine-J	4.75	3.82	1296	19.75	3.505	1.118	350	18.23
Mine-K	3.7	2.49	400	28	3.3	0.965	350	21
Mine-L	5.4	5.74	729	22.41	3.505	1.12	340	51

The required input data from the above Table 5 were given to all equations (Equations 1 - 9) to anticipate the projected Z value for all three mines considered for validation. The predicted daily production value (average production daily in tonnes) was calculated using this predicted Z value. Then, using a significance level of 5% (i.e., $a = 0.05$), *t*-tests were run between actual Z (obtained from the field visit) and predicted Z as well as between actual daily production (recorded during the field visit) and predicted daily production. The accompanying Table 6 shows information on the actual and predicted Z, as well as the actual and predicted daily production, together with their t-test findings. The null hypothesis (H_0) and alternate hypothesis (H_a) for the *t*-tests are mentioned below-
H_0 = the difference between the means is 0
H_a = the difference between the means is not 0.
The null hypothesis cannot be rejected when the *p*-value is more than *a*.

Discussion on results of modelling and validation

The equation generation by curve-fitting considers one input parameter along with the production-related parameter (Actual Z) as the output, giving the R^2 value. Through their corresponding R^2 value, each input parameter's significance for predicting the Z value may be understood. Table- 2 shows the R^2 value for each geo-mining condition in relation to Actual Z. The greatest R^2 value was shown for seam thickness (0.8779), followed by pillar area (0.84), gradient (0.8112), and coal strength (0.6008). This indicates that the seam thickness has a better correlation with Z than other geo-mining parameters. Similarly, Table 3 depicts the R^2 value for each machine parameter when correlated with the actual Z value, where cutter motor power depicted the highest R^2 value (0.8033), followed by drum width (0.7462), drum diameter (0.7339) and cutter rpm (0.5991). These findings make it clear that the cutter motor power exhibits a better correlation with connection to the Z value than other machine characteristics (drum width, drum diameter and cutter rpm). Further, their corresponding adjusted R square values and Root Mean Square Error (RMSE) values (depicted in Tables 2 and 3) also support the above conclusions drawn based on the R^2 value and apprehend acceptable correlation between each input and output interrelationships.

The validation results (Table 6) show that the *p*-value for the *t*-test performed between actual and predicted daily production as well as actual and predicted Z are much higher than the selected significance value (a = 0.05). Therefore, the null hypothesis cannot be rejected, and the difference between the means of predicted and actual Z, as well as predicted and actual daily production is 0. Moreover, by observing Table 6, it can also be easily concluded that the difference between the predicted and actual results is considerably lower. The results of the *t*-test and other relevant information mentioned in Table 6 validate the equations and prove their relevance with the actual CM-based underground coal mining phenomenon.

Tab.6. Validation results for each equation

Equation No.	Mine-Name	Actual Z	Predicted Z	Actual daily production (t)	Predicted daily production (t)	*p*-value of t-test between predicted and actual Z	*p*-value of *t*-test between predicted and actual production (t)
Eq.1.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.149 3.221 3.192	1495 1385 927	1408 1663 1556	0.242	0.221
Eq.2.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.116 3.129 3.097	1495 1385 927	1305 1345 1250	0.782	0.870
Eq.3.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.257 3.051 3.152	1495 1385 927	1807 1125 1420	0.537	0.528
Eq.4.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.206 3.116 3.177	1495 1385 927	1607 1305 1503	0.361	0.358
Eq.5.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.154 3.152 3.154	1495 1385 927	1427 1419 1427	0.409	0.422
Eq.6.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.156 3.209 3.155	1495 1385 927	1432 1616 1430	0.303	0.292
Eq.7.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.060 3.060 3.023	1495 1385 927	1149 1149 1054	0.516	0.439
Eq.8.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.106 3.113 3.196	1495 1385 927	1276 1299 1569	0.567	0.601
Eq.9.	Mine-J Mine-K Mine-L	3.175 3.141 2.967	3.088 2.888 3.082	1495 1385 927	1224 772 1209	0.460	0.429

Note: For all *t*-tests, the value of a was considered as 0.05

Conclusion

This study uses curve-fitting and regression modelling to identify correlations between variables in order to anticipate the production output from a Continuous Miner-based underground coal mining project. Discussions with experienced mining engineers and personnel led to identifying the independent parameters for this objective. Further, statistical testing for goodness of fit in connection to curve-fitting demonstrates the importance of each input parameter in predicting the Z value (output). The goodness of fit results revealed that seam thickness and cutter motor power correlate better with production-related parameters; their corresponding R^2 values are 0.8779 and 0.8033. All chosen independent variables showed a stronger link with the actual Z value. A combined effect model was subsequently created, using all input parameters collectively as inputs and a production-related parameter as output. This model's goodness of fit results were outstanding (R^2 = 0.982).

Additionally, datasets from three CM-based underground coal mines that were not considered during equation generation were fed into the interrelationships. The interrelationships' predictions' results were satisfactory, validating their ability to predict the production output in a working environment. Furthermore, it can be inferred that the generated interrelationships may be a useful tool for choosing equipment both for a brand-new project and a project already in operation. However, future inclusion of some other parameters, such as environmental parameters and data linked to inventory management, may improve the interrelationships' ability to predict outcomes more accurately.

References

Abdulredha, M., Al Khaddar, R., Jordan, D., Kot, P., Abdulridha, A., & Hashim, K. (2018). Estimating solid waste generation by hospitality industry during major festivals: A quantification model based on multiple regression. *Waste Management*, 77, pp. 388–400. https://doi.org/10.1016/j.wasman.2018.04.025

Achanti, V.B., & Khair, A.W. (2001). Cutting efficiency through optimised bit configuration — an experimental study using a simulated continuous miner. *Mineral Resources Engineering*, 10(04), pp. 427–434. https://doi.org/10.1142/S0950609801000737

Álvarez, C., Espinel, E., & Noriega, C.J. (2021). Study of different alternatives for dynamic simulation of a steam generator using MATLAB. *Fluids*, 6(5), p. 175. https://doi.org/10.3390/fluids6050175

Banerjee, S. (2017). Performance augmentation of continuous miner based system in India: A reliability based approach. *Mining - Informatics, Automation and Electrical Engineering*, 3(531), pp. 42-48. http://dx.doi.org/10.7494/miag.2017.3.531.42

Banerjee, S. (2019). Performance evaluation of Continuous Miner Based Underground Mine Operation System: An OEE based approach. *New Trends in Production Engineering*, 2(1), pp. 596–603. Doi:10.2478/ntpe-2019-0065.

Banerjee, S., & Dey, N.C. (2022). An OEE-based approach to identify impact of vulnerable sub-systems on the continuity of coal mining operation. *Journal of The Institution of Engineers (India): Series D*, 103(1), pp. 45–55. https://doi.org/10.1007/s40033-021-00315-9

Bartoš, K., Pukanská, K., & Sabová, J. (2014). Overview of available open-source photogrammetric software, its use and analysis. *International Journal for Innovation Education and Research*, 2(4), pp. 62–70. https://doi.org/10.31686/ijier.vol2.iss4.170

Blistanova, M., *Zeleňáková, M., Blistan, P., & Ferencz*, V.(2016). Assessment of flood vulnerability in Bodva river basin, Slovakia. *Acta Montanistica Slovaca*, 21(1), pp. 19–28. Doi:10.3390/ams21010019.

Carpick, R.W., Ogletree, D.F., & Salmeron, M. (1999.) A general equation for fitting contact area and friction vs Load Measurements. *Journal of Colloid and Interface Science*, 211(2), pp. 395–400. https://doi.org/10.1006/jcis.1998.6027

Cehlár, M., Janočko, J., Šimková, Z., & Pavlik, T. (2017). Assessment process of concept for mining and its impact on the region. *E3S Web of Conferences*, 15, p. 01019. https://doi.org/10.1051/e3sconf/20171501019

Cui, F., Park, C., & Kim, M. (2019). Application of curve-fitting techniques to develop numerical calibration procedures for a river water quality model. *Journal of Environmental Management*, 249, p. 109375. https://doi.org/10.1016/j.jenvman.2019.109375

Dahal, H., & Routray, J. (2013). Identifying associations between soil and production variables using linear multiple regression models. *Journal of Agriculture and Environment*, 12, pp. 27–37. https://doi.org/10.3126/aej.v12i0.7560

Dey, N. C., & Sharma, G. D. (2013). A critical study on the underground environment of coal mines in India-An ergonomic approach. *Journal of The Institution of Engineers (India): Series D*, 94, pp. 1-6. https://doi.org/10.1007/s40033-013-0023-3

Dey, S. C., Dey, N. C., & Sharma, G. D. (2018). Occupational Malfunctioning and Fatigue Related Work Stress Disorders (FRWSDs): An Emerging Issue in Indian Underground Mine (UGM) Operations. *Journal of the Institution of Engineers (India): Series D*, 99, pp. 103-108. https://doi.org/10.1007/s40033-017-0149-9

Dyczko, A., MALEC, M., & PROSTAŃSKI, D. (2020). The efficiency of longwall systems in the case of using different cutting technologies in the LW Bogdanka. *Acta Montanistica Slovaca*, 25(4), pp. 504-516. https://doi.org/10.46544/AMS.v25i4.06

Feng, Q., & Chen, H. (2013). The safety-level gap between China and the US in view of the interaction between coal production and Safety Management. *Safety Science*, 54, pp. 80–86. https://doi.org/10.1016/j.ssci.2012.12.001

Gao, D., Guo, L., Wang, F., & Zhang, Z. (2021). Study on the spontaneous combustion tendency of coal based on grey relational and multiple regression analysis. *ACS Omega*, 6(10), pp. 6736–6746. https://doi.org/10.1021/acsomega.0c05736

Guo, S., Guo, G., Li, H., & Yang, X. (2021). Transforming post-mining area into expressway site by stability evaluation with Clustering method: A case study. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1–19. https://doi.org/10.1080/15567036.2021.1923868

Hull, B.P., Leigh, J., Driscoll, T.R., & Mandryk, J. (1996). Factors associated with occupational injury severity in the new South Wales underground coal mining industry. *Safety Science*, 21(3), pp. 191–204. https://doi.org/10.1016/0925-7535(95)00064-X

Islavath, S.R., & Bodakunta, S. (2022). Estimation of optimum line of extraction for continuous miner workings and development of Continuous Miner Stability index (CMSI) using 3D Numerical Modeling and Statistical Approach. *Mining, Metallurgy & Exploration, 39(3),* pp. 1149–1169. https://doi.org/10.1007/s42461-022-00602-3

Karacan, C.Ö., & Luxbacher, K. (2010). Stochastic modeling of Gob Gas Venthole production performances in active and completed longwall panels of coal mines. *International Journal of Coal Geology*, 84(2), pp. 125–140. https://doi.org/10.1016/j.coal.2010.09.001

Kazanin, O., Sidorenko, A., & Drebenstedt, C. (2021). Intensive underground mining technologies: Challenges and prospects for the coal mines in Russia. *Acta Montanistica Slovaca*, 26(1), pp. 60-69. https://doi.org/10.46544/AMS.v26i1.05

Kholod, N., Evans, M., Pilcher, R. C., Roshchanka, V., Ruiz, F., Coté, M., & Collings, R. (2020). Global methane emissions from coal mining to continue growing even with declining coal production. *Journal of Cleaner Production*, 256, 120489. https://doi.org/10.1016/j.jclepro.2020.120489

Kim, K.D., Lee, S., Oh, H.J., Choi, J.K., & Won, J.S. (2006). Assessment of ground subsidence hazard near an abandoned underground coal mine using GIS. *Environmental Geology*, 50(8), pp. 1183–1191. https://doi.org/10.1007/s00254-006-0290-5

Kolasa-Wiecek, A. (2015). Stepwise multiple regression method of greenhouse gas emission modeling in the energy sector in Poland. *Journal of Environmental Sciences*, 30, pp. 47–54. https://doi.org/10.1016/j.jes.2014.09.037

Li, Z., Wang, E., Ou, J., & Liu, Z. (2015). Hazard evaluation of coal and gas outbursts in a coal-mine roadway based on logistic regression model. *International Journal of Rock Mechanics and Mining Sciences*, 80, pp. 185–195. https://doi.org/10.1016/j.ijrmms.2015.07.006

Mandal, P.K., Das, A.J., Kumar, N., Bhattacharjee, R., Tewari, S., & Kushwaha, A. (2018). Assessment of roof convergence during driving roadways in underground coal mines by Continuous Miner. *International Journal of Rock Mechanics and Mining Sciences*, 108, pp. 169–178. https://doi.org/10.1016/j.ijrmms.2018.06.001

Modi, J., Bharti, S., & Kant, R. (2017). Applicability of continuous miner in room and pillar mining system: higher production and productivity with safety. *In International Conference on Deep Excavation, Energy Resource and Production. Kharagpur:* IIT Kharagpur.

Mohutsiwa, M., & Musingwini, C. (2015). Parametric estimation of capital costs for establishing a coal mine: South Africa Case Study. *Journal of the Southern African Institute of Mining and Metallurgy*, 115(8), pp. 789–797. http://dx.doi.org/10.17159/2411-9717/2015/V115N8A17

Palei, S.K., & Das, S.K. (2009). Logistic regression model for prediction of roof fall risks in bord and pillar workings in coal mines: An approach. *Safety Science*, 47(1), pp. 88–96. https://doi.org/10.1016/j.ssci.2008.01.002

Paul, P.S. (2009). Predictors of work injury in underground mines — an application of a logistic regression model. *Mining Science and Technology (China)*, 19(3), pp. 282–289. https://doi.org/10.1016/S1674-5264(09)60053-3

Que, S., Awuah-Offei, K., & Frimpong, S. (2015). Optimising design parameters of continuous mining transport systems using discrete event simulation. *International Journal of Mining, Reclamation and Environment*, 30(3), pp. 217–230. https://doi.org/10.1080/17480930.2015.1037056

Ramesh, N., Ramesh, S., Vennila, G., Bari, J.A., & MageshKumar, P. (2016). Energy production through organic fraction of municipal solid waste—a multiple regression modeling approach. *Ecotoxicology and Environmental Safety*, 134, pp. 350–357. https://doi.org/10.1016/j.ecoenv.2015.08.027

Ranjith, P. G., Zhao, J., Ju, M., De Silva, R. V., Rathnaweera, T. D., & Bandara, A. K. (2017). Opportunities and challenges in deep mining: a brief review. *Engineering*, 3(4), pp.546-551. https://doi.org/10.1016/J.ENG.2017.04.024

Sánchez, F., & Hartlieb, P. (2020). Innovation in the mining industry: Technological trends and a case study of the challenges of disruptive innovation. *Mining, Metallurgy & Exploration*, 37, pp. 1385-1399. https://doi.org/10.1007/s42461-020-00262-1

SELYUKOV, A., ZHIRONKIN, S., & CEHLÁR, M. (2020). Improvement of Continuous Lateral Surface Mining Method for Coal Extraction from Closed Mines' Pillars. *Acta Montanistica Slovaca*, 25(4), pp. 542-562. https://doi.org/10.46544/AMS.v25i4.09

Sharma, G. D., Dey, S., & Dey, N. C. (2016). Rationalising postural demand of side discharge loading machine operators with respect to musculoskeletal pain and discomfort in underground coal mines in India. *International Journal of Human Factors and Ergonomics*, 4(1), pp. 60-72. https://doi.org/10.1504/IJHFE.2016.076573

Simionescu, M., Strielkowski, W., & Gavurova, B. (2022). Could quality of governance influence pollution? evidence from the revised Environmental Kuznets curve in central and Eastern European countries. *Energy Reports*, 8, pp. 809–819. https://doi.org/10.1016/j.egyr.2021.12.031

Singh, R., Singh, J.K., Singh, T.N., & Dhar, B.B. (1995). Cuttability assessment of hard coal seams. *Geotechnical and Geological Engineering*, 13(2), pp. 63–78. https://doi.org/10.1007/BF00421873

Tyulenev, M., Litvin, O., Cehlár, M., Zhironkin, S., & Gasanov, M. (2017). Estimation of Hydraulic Backhoes Productivity for Overburden Removing at Kuzbass Open Pits. *Acta Montanistica Slovaca*, 22(3), pp. 296–302.

Wang, J., & Feng, L. (2016). Curve-fitting models for fossil fuel production forecasting: Key Influence Factors. *Journal of Natural Gas Science and Engineering*, 32, pp. 138–149. https://doi.org/10.1016/j.jngse.2016.04.013

Zhang, Z.X., Hou, D.F., Aladejare, A. Ozoji, T., & Qiao, Y. (2021). World mineral loss and possibility to increase ore recovery ratio in mining production. *International Journal of Mining, Reclamation and Environment*, 35(9), pp. 670–691. https://doi.org/10.1080/17480930.2021.1949878

Zhao, L., & Liu, H. (2019). Simulation of the working performance of a shearer cutting coal rock. *Modelling and Simulation in Engineering*, 2019(1), pp. 1–13. https://doi.org/10.1155/2019/2089304