International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I12P113
Volume 73 Issue 12, 162-173, December 2025

Original Article

Bivariate Analysis of the Geotechnical Properties and the Key Performance Indicators of the Surface Miners

Om Prakash Singh[1*], P Y Dhekne[2], Manoj Pradhan[2]

[1,2]*National Institute of Technology, Raipur, India.*

**Corresponding Author : opsingh085@gmail.com*

Received: 12 August 2025 Revised: 18 November 2025 Accepted: 25 November 2025 Published: 19 December 2025

Abstract - *An increase in the population and operating mining projects near cities, towns, and villages, many opencast mines are planning blast-free operations through the application of surface miners. These machines are costly. Hence, the assessment of the geotechnical parameters that influence the performance of the machine is a prerequisite. Accordingly, research was planned and executed in the opencast coal projects of Mahanadi Coalfields Ltd. (MCL) to investigate the effect of geotechnical parameters, viz. Uniaxial Compressive Strength (UCS), Cerchar Abrasivity Index (CAI), Young's Modulus (E), and in-situ P-wave Velocity (IVP), on two key performance indicators of surface miner - Normalised Production Rate (NPR) and Pick Consumption per 1000 t (PCM). A database comprising the above-stated geotechnical parameters and the key performance indicators of the surface miner was generated. Bivariate regression analysis was conducted on the database, and as a result, it was observed that CAI predominantly influences the NPR and PCM with $R^2 = 0.91$ and 0.89, respectively. UCS follows with $R^2 = 0.88$ for NPR and 0.80 for PCM, while IV_P ($R^2 = 0.85$ and 0.77) and E ($R^2 = 0.82$ and 0.75) show comparatively lower but significant effects. These findings establish CAI as the dominant parameter affecting both productivity and tool wear, followed by UCS, IV_P, and E. Accurate determination of these parameters is therefore essential for reliable performance prediction, optimal machine selection, and cost-effective surface mining operations in the geotechnical set-up of the coal seams in MCL.*

Keywords - *Cerchar Abrasivity Index, In-Situ P-wave Velocity, Performance Indicators of the Surface Miners, Uniaxial Compressive Strength, Young's Modulus of Elasticity.*

1. Introduction

The conventional drilling and blasting method has been in vogue for the extraction of coal as well as overburden. When conventional drilling and blasting methods are employed, waste materials become intermixed with coal, consequently lowering its grade (Kanchibotla & Scott, 1999; Khoyutanov & Gavrilov, 2019). The subsequent processing and cleaning required to remove these contaminants increase operational costs and diminish overall profitability. Further, in early days, the drilling and blasting method did not pose problems like social unrest, however, with the increased population a lot of human dwellings are being constructed near the mining areas and the inhabitants of the dwellings complain to the mine management about the ill effects of blasting on them viz. ground vibrations, air overpressures, flyrock, and dust (Agrawal & Mishra, 2018; Kiani et al., 2019; Mishra et al., 2023).

To mitigate the ill effects, the management of most of the mines is now resorting to the use of surface miners, at least during mineral extraction. The machine offers a cost-effective and reliable mass production technology due to the ease of application and produces a sized product at a faster rate, eco-friendly mining, and improved recovery of coal and minerals, especially in areas sensitive to blasting (Pradhan et al., 2014). So, more and more surface miners are being introduced into the coal mines. The surface miner was first employed in India in 1994 at a limestone mine (Dey & Sen, 2008). Whereas, the first successful application of a surface miner in Indian coal mining took place in 1999 at the Lakhanpur coal mines of Mahanadi Coalfields Limited (MCL) (Ghose, 2000).

Initially, the contracts were awarded to operate the surface miners in the mines. Later on, the departmental activities of mining by surface miners also received impetus. It is therefore pertinent that not much attention has been paid to improving the performance parameters of the surface miners, as they were limited in number until they were implemented through the department, and their numbers increased. With the increasing scale of the surface miner operations, it has become necessary to undertake investigations to examine the interrelations between the geotechnical and performance parameters of a surface miner (Yadav et al., 2020).

Excavation with surface miners has proved to be a highly efficient coal production method, and therefore, research has been carried out on increasing its productivity and performance. Several researchers have investigated the cutting performance of surface miners over the years. A relationship was established by Jones and Kramadibrata (1995) to quantify the influence of Uniaxial Compressive Strength (UCS) of rocks on the productivity of continuous surface miners. Building on this, Kramadibrata & Shimada (1996) demonstrated a functional relationship between the ‘Voest Alpine Rock Cuttability Index (RCI)’ and various parameters of intact rock, rock mass, and machine characteristics. On a laboratory scale, Tiryaki & Dikmen (2006) examined the relationship between tensile strength and Specific Energy (SE) using linear pick cutting. Later, considering multiple parameters associated with intact rock, rock mass, and machine design and operational conditions (Murthy et al., 2009), proposed the Cuttability Index of Surface Miner (CISM). Dey and Ghose (2009) developed a nomogram to evaluate the suitability of a surface miner for a given rock mass, accounting for key factors such as point load strength index, volumetric joint count, rock abrasiveness, and the orientation of machine operation relative to joint directions.

More recently, Singh et al. (2023) investigated the correlation between coal production and critical productivity indicators, namely, machine shift time, pick consumption, and diesel consumption under three distinct geo-mining conditions, and further established the relationship between surface miner utilisation and production efficiency. Most of these studies have resulted in generalised predictive models based on data from multiple rock types (Prakash, 2013; Origliasso et al., 2014; Prakash & Murthy, 2017; Prasad et al., n.d.; Singh et al., 2019). (Vishwakarma et al., 2023) examined the effect of applied thrust on rock penetration rate in operations deploying Raise Boring Machine (RBM) for two different rock types, viz., Amphibolite (AMP) and Garnet-Biotite-Sillimanite-Gneiss (GBSG). Using ANSYS Explicit Dynamics, a numerical model simulated the relationship between thrust and induced tensile stress, revealing a power-law correlation between thrust and penetration rate. The study identified an optimal thrust per cutter of 12–14 tons, enabling efficient excavation and energy utilisation. The findings provide a predictive basis for optimising RBM performance under varied geological conditions.

2. Research Gap

These studies are focused on machine parameters, but they have overlooked the significance of rock mass parameters, treating them as constant. Some recent studies, which have accounted for nearly all parameters related to intact rock, rock mass, machinery, and geo-mining conditions, have developed capable yet overly generalised models. For instance, Prakash & Murthy (2024) developed multiple regression models for predicting the cutting speed of surface miners in coal and limestone. Although this study has been beneficial, it presents the effects of the geotechnical parameters on the key performance indicators of surface miners in a generalised manner. The surface miner is a costly machine. Hence, a generalised assessment of the effect of geotechnical parameters on the performance indicators of a surface miner does not serve the purpose; rather, it requires a site-specific investigation. This will help in identifying the parameters that are playing an essential role in cutting performance. Accordingly, this study has been carried out to assess the influence of various parameters on cutting performance with the help of bivariate Analysis. This Analysis will help to find out the most dominant parameters and their influence on the cutting performance.

While state-of-the-art methods such as multivariate regression, machine learning, or neural network models often provide superior predictive accuracy, bivariate regression excels in explanatory clarity and physical interpretability (Padarian et al., 2020). The cause-and-effect relation during the cutting of the rock using the surface is aptly explained without any noise (Pentoś et al., 2022). Alternatively, the machine learning techniques are merely ‘Black Box’, where the internal processes and the influence of the variables are not transparent, which limits their ability to uncover the underlying mechanism (Welchowski et al., 2022).

Bivariate Analysis overcomes the issues of multicollinearity, overfitting, and excessive data dependency. It is used to develop simple and physically significant equations that can be easily validated. This makes the equations easily reproducible and useful (Harle & Wankhade, 2025). Therefore, in the studies conducted to understand the mechanism rather than the prediction, Bivariate regression analysis offers a simple yet rigorous method to quantify the influence of geotechnical parameters on surface miner performance.

3. Site of Investigations

The Talcher and Ib valley coalfields of MCL have opencast coal projects which use surface miners. To carry out the research work, ten different opencast projects of the MCL using surface miners have been selected. The projects are located in Talcher and the Ib Valley coalfield. The Talcher coalfield consists of thickly bedded sedimentary deposits up to over 1500 m thick. The lithology of these strata is constituted by various rock types, namely sandstone, shale, coal seams, conglomerate boulder beds, etc.

The coalfield comprises the Talcher, Karharbari, Barakar, Barren Measures, and Kamthi formations. Out of the above formations, the Barakar and Karharbari contain coal deposits. While the coal seam of Karharbari formations is better in quality, the coal seams of Barakar largely record high ash coals (Bhatta et al., 2022). The Ib Valley coalfields constitute a half-elliptical basin, closed towards the south-east and open towards the north-west. In the north-western, northern, north-eastern, eastern, and south-eastern sectors, the basin is in normal contact with the surrounding metamorphic rocks. In contrast, along the southwestern boundary, the basin exhibits a faulted contact with the metamorphics, where younger formations, namely the Raniganj and Barren Measures, occur in collocation with the metamorphic rocks.

The coalfields are contiguous with the Mand-Raigarh coalfield of Chhattisgarh, with the administrative boundary between Odisha and Chhattisgarh serving as the demarcation line between the two coalfields.

The Ib Valley coalfields encompass two coal-bearing formations, Barakar and Karharbari, covering a potential coal-bearing area of approximately 300 km², extending along the southern, eastern, and northern peripheries of the basin (Senapaty & Behera, 2015).

The overburden removal is being carried out by drilling, blasting, and mucking by shovel-dumper combinations. In each of the projects, the extraction of coal is carried out with surface miners, following mainly the turn-back method with windrowing operation.

Currently, five different models of surface miners from L&T, Wirtgen, and Puzzolana are in operation at the sites selected for this research. These surface miners feature cutting drum widths of 3 m, 3.8 m, and 4 m, with corresponding drum radii of 0.575 m, 0.600 m, and 0.650 m. All models fall within the 50–80-ton operating weight class. The general description of the projects and the detailed specifications of the surface miner models are given in Tables 1 and 2. Figure 1 shows a surface miner employed in one of the coal mines.

Table 1. General description of the projects

Name of the Coalfield	Opencast Project Name	Mineable Reserve (in Mt)	Stripping Ratio (m^3/t)	Working Coal Seams during the study Period	Gradient of the coal seams	Average Thickness (m)	Mine Capacity (in Mt)	Life of Mine (years)
Talcher	Ananta	366.67	2.21	IV, VB, VI, T	1 in 5 to 11	6.15, 4.21,4	15	26
	Balram	192.64	2.21	II E, III E, IV	1 in 10	6.97, 3.88, 3.19	8	25
	Lingaraj	321.5	0.69	II, III, V, VI A	1 in 4	39.28, 12.5,10.22, 8.5	16	21
	Bhubaneswari	374.12	0.67	II	1 in 12 to 15	30	20	25
IB Valley	Lajkura	69.4	3.4	Lajkura	1 in 16	6.57 to 12.54	2.5	29
	Samleswari	112.26	3.4	Lajkura	1 in 18	6.4 to 13.16	12	10
	Belpahar	63.33	2.19	Rampur	1 in 10 to 14	0.2 to 8.74	8	10
	Lakhanpur	358.58	2.34	Lajkura	1 in 11	20.88 to 33.53	15	25
	Garjanbahal	229.25	0.98	Lajkura, Rampur	1 in 11 to 19	11.5	10	28
	Kulda	323.05	0.96	Lajkura, Rampur	1 in 10 to 11	2.98 to 31.89, 2.3 to 17.83	15	21

Table 2. Specifications of the surface miners employed in the opencast coal projects

Sr No.	Make	Model	Drum Width (m)	Drum Radius (m)	Engine Power (kW)	Maximum Cutting depth (m)	Number of cutting picks (No.)	Operating Weight (kg)	Maximum Operating speed (m/min)
1	L&T	KSM-303	3.0	0.575	597	0.30	106	53500	30
2	L&T	KSM-403	4.0	0.575	709	0.30	136	57500	25
3	Puzzolana	PMM-2205	4.0	0.600	671	0.30	111	76000	85
4	Wirtgen	220 SM 3.8	3.8	0.650	709	0.35	100	53800	85
5	Wirtgen	220 SM 3.8	3.8	0.650	709	0.35	100	58050	85

Fig. 1 L&T KSM 403 model surface miner (source: L&T product brochure)

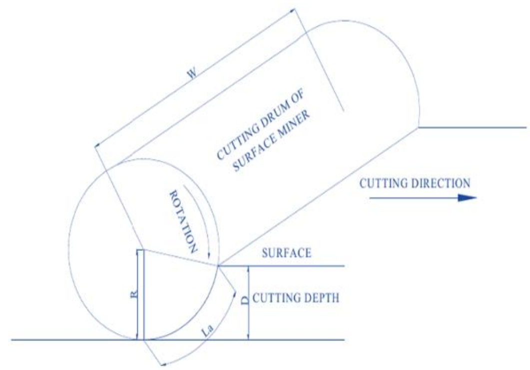

Fig. 2 Cutting dimensions of the face

4. Selection of Key Performance Indicators and Geotechnical Parameters

An extensive literature survey indicates that production rate (tonnes per hour), pick consumption per 1000 t (PCM), and the diesel consumption per 1000 tonnes are the key performance indicators of a surface miner. The production obtained from the cutting done by a surface miner depends upon the dimensions and depth of the cut. In the present investigations, the production has been obtained from the surface miners having drums of different dimensions, hence the dimensions and the depth of cut, and subsequently the area of the cut, also vary. Hence, instead of production rate (t/h), the Normalised Production Rate (NPR) expressed in t/m^2/h has been considered (Prakash & Murthy, 2017). The NPR is calculated using the following equations.

$$NPR = \frac{TPH}{CA}$$

$$CA = L_a \times D_w$$

$$L_a = \frac{2\pi R\left[\frac{(R-D)}{R}\right]}{360}$$

Where NPR is the Normalised Production Rate (t/h/m2), TPH is the measured rate of production (t/h), CA is the area of the drum that remains in contact with the rock during cutting operation (m2), Dw is the width of cutting drum (m), R is the radius of cutting drum (m), La is the length of arc in contact with the drum during cutting, and D is the depth of cut (m). The cutting dimensions of the face are given in Figure 2 (Prakash & Murthy, 2024).

The pick consumption is calculated by dividing the number of picks replaced by 1000 t production. The diesel consumption has not been considered as one of the key performance indicators, as the diesel consumption depends upon many other factors like age of the machine, maintenance standards of the engine, the operator's skill, etc., besides the tonnage that has been cut.

Literature cites that many in-situ properties, like strength properties and fracture properties, affect the cutting performance of a surface miner, and IV$_P$ is the best assessment of the in-situ conditions. Hence, in-situ properties of the rockmass have been represented by the IV$_P$. As regards the intact rock properties, the abrasivity of the rockmass is one of the parameters that affects the cutting performance. The abrasivity has been expressed as dimensionless CAI. The E of a rockmass represents its rigidity, that is, the resistance to deformation, and hence it has been considered. While cutting the rockmass, the pick of the cutting drum pierces into the rockmass and overcomes the UCS before the rock fails. So, the UCS of the rockmass has been considered as it plays an important role in the rock breakage.

5. Data Collection

The above-stated geotechnical parameters of the rockmass have been determined using the standard methods as given in Table 3.

Table 3. Standard methods used for the assessment of geotechnical parameters

Test	Standard followed
Preparation of samples	IS:9179-1979
UCS	IS:9143-1979
E	IS:9221-1979
CAI	ASTM D7625-10
IV$_P$	ASTM D7400-14

In addition to the above, the density has also been determined to measure the production rate. A total of 169 data sets comprising the NPR, PCM, UCS, CAI, E, and IVP have been generated. Out of which 143 data sets were used for conducting further Analysis by removing the outliers, i.e., data points beyond ±3 standard deviations. The in-situ rockmass properties determined under this study were the Schmidt Rebound Number (RN) and the In-situ Seismic Refraction Tomography (ISRT) through measurement of In-Situ p-wave Velocity (IVp) and in-situ S-wave Velocity (IVs) of coal seams. For the study, 24-channel wireless ATOM geophones were employed. Small boreholes, 1 to 2 inches in depth, were drilled at either 2 m or 3 m intervals to accommodate the geophones, depending on the seam thickness and the required investigation depth. Plaster of Paris was applied to ensure effective coupling of the geophones with ground movements. A 10 kg sledgehammer was used to generate impacts at predetermined offsets. For geophones placed at 2 m intervals, impacts were applied at -20, -16, -12, -8, -4, +8, +12, +16, and +20 m, whereas for geophones placed at 3 m intervals, impacts were applied at -30, -24, -18, -12, -6, +6, +12, +18, +24, and +30 m. Figure 3 illustrates the installation of ATOM geophones for ISRT. Moreover, during the study, the movement of surface miners was monitored using a high-precision GPS/Galileo/GLONASS system. The turn-back mining method has been depicted in Figure 4, with a working face measuring 468 m in length and 69 m in width. The overview of the data is given in Table 4.

Fig. 3 Installation of ATOM geophones for ISRT

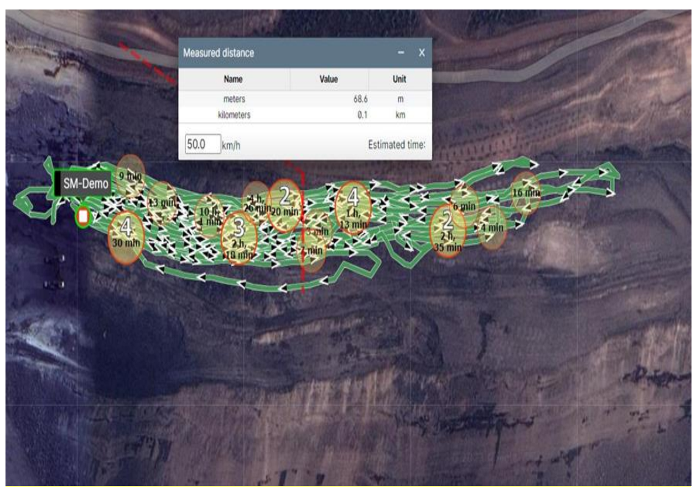

Fig. 4 Length of operation with the Turn-Back method at an OCP of MCL

Table 4. Overview of the data generated

Statistical Parameter	Mean	Standard Error	Median	Mode	Standard Deviation	Kurtosis	Skewness	Range	Minimum	Maximum
UCS	21.432	0.291	22.450	24.330	3.478	0.355	-1.108	15.810	13.500	29.310
CAI	0.177	0.002	0.180	0.185	0.021	-0.032	-0.689	0.095	0.125	0.220
E	2.169	0.053	2.230	1.590	0.639	-0.839	0.093	2.671	1.110	3.781

IV_P	963.902	16.786	1003.000	977.000	200.731	-0.164	-0.345	1044.000	511.000	1555.000
NPR	2.047	0.048	2.100	2.160	0.572	0.054	-0.280	2.800	0.670	3.470
PCM	20186.380	379.982	18737.240	N/A	4543.925	0.869	1.316	19132.100	13219.820	32351.920

The standard deviation and the range indicate that there is adequate dispersion. Kurtosis values, which are very close to 0, indicate that the values are almost normally distributed. This is substantiated by the fact that the mean and median are almost equal. The skewness nearing zero indicates that there is no substantial positive and negative skewness in the normal distribution.

6. Bivariate Regression of NPR

Graphs have been plotted with each of the geotechnical parameters as independent variables and the NPR as the dependent variable. The bivariate regression equations have been obtained along with the Coefficient of determination (R2). The Analysis of the NPR vis-à-vis the geotechnical parameters is presented in Figures 5 to 8.

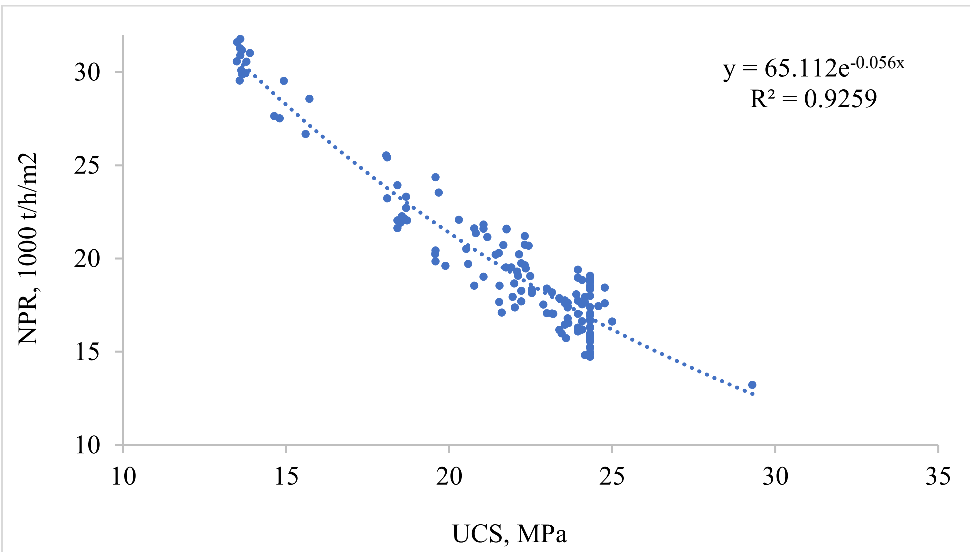

Fig. 5 Bivariate regression of NPR on UCS

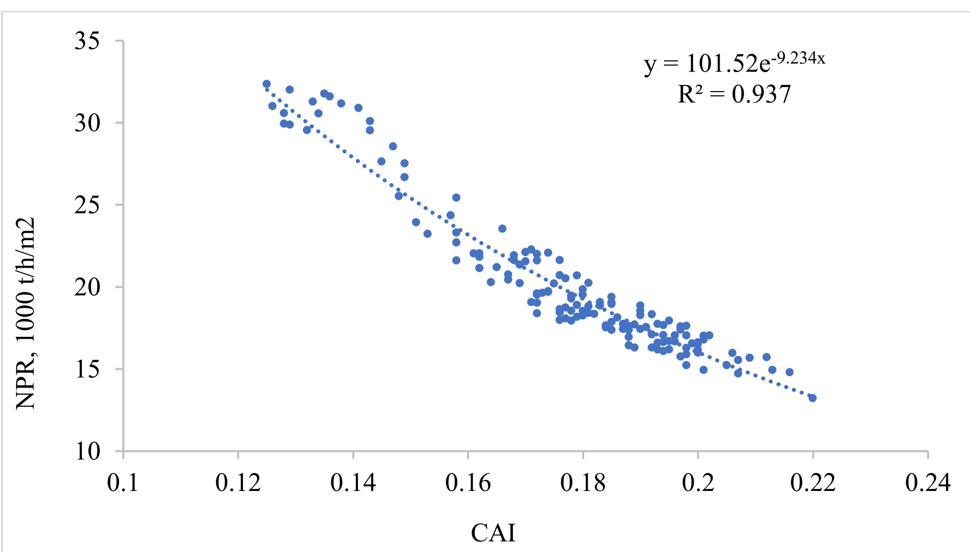

Fig. 6 Bivariate regression of NPR on CAI

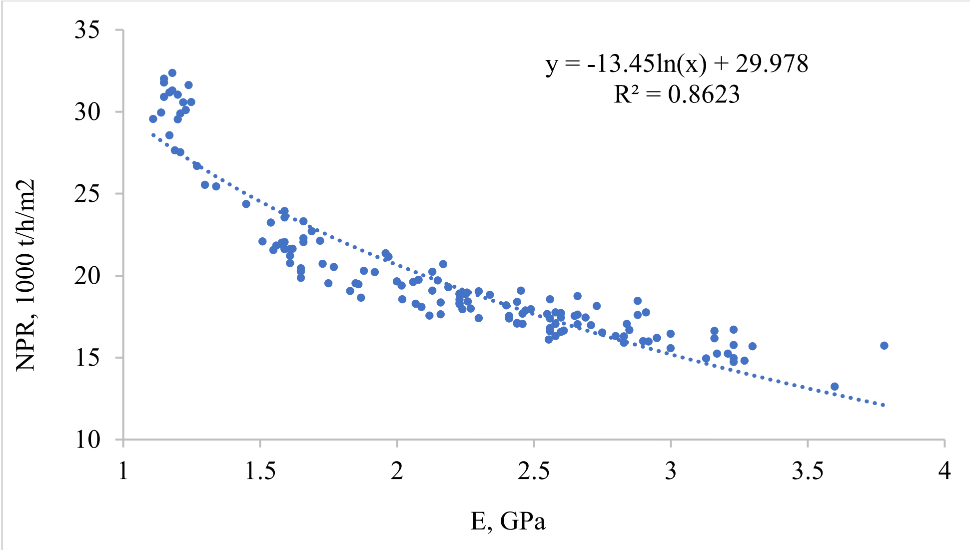

Fig. 7 Bivariate regression of NPR on E

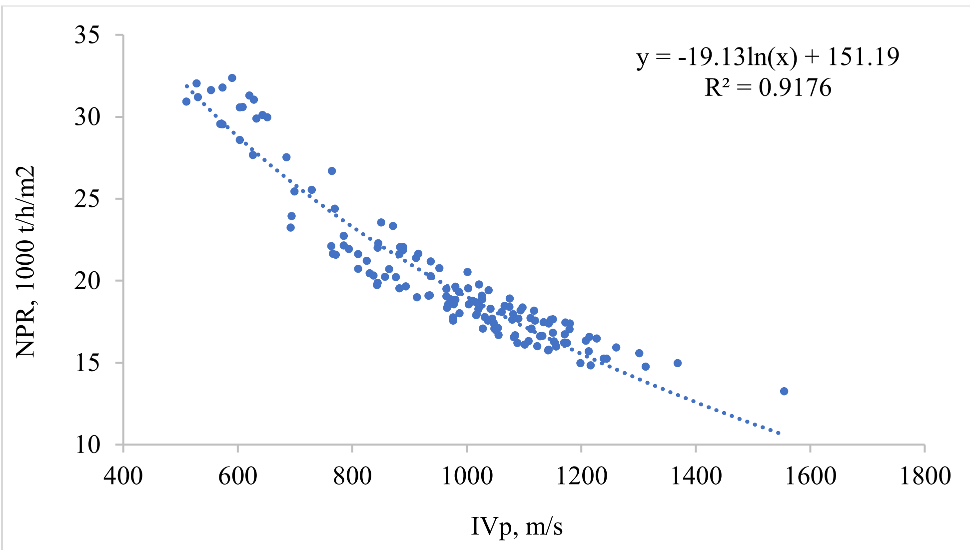

Fig. 8 Bivariate regression of NPR on IV_P

Figure 5 illustrates that the regression coefficient is high, indicating a strong correlation between UCS and NPR. The exponential regression equation with a low negative index means that the fall in NPR is mild with UCS. It has been observed that the requirement of cutting force increases with uniaxial compressive strength. So, when a surface miner encounters a rockmass that has more compressive strength than the usual rockmass, the demand for the cutting force increases. However, a surface miner can supply the cutting force up to a specific limit. Any necessity beyond the limit cannot be met, resulting in a decline in production. The relation between the UCS and the PR has been examined by (Amar, 2013) and (Origliasso et al., 2014).

Prakash and Murthy (2013) developed the following equation.

$$SE = 0.123 + 0.97\sigma_c$$

Where SE is the specific energy and the σ_c is the UCS.

The above equation indicates that as the UCS increases, the specific energy also increases. (Origliasso et al., 2014) Developed a relation between the specific energy and the production rate of a surface miner and proposed the following equation.

$$SE = \frac{P_w}{PR}$$

Where SE is the Specific Energy, P_w is the engine power of the surface miner, and PR is the production rate. From the above two equations, it is clear that the UCS has an inverse relation with the NPR of a surface miner.

Similar results on the relationship between UCS and the PR have been reported by (Amar, 2013; Origliasso et al., 2014), who have reported that the relation between PR (m^3/h) and SE (kJ/m^3) has been an exponential decay in the case of a road header face.

It is observed from Figure 6 that the regression coefficient is high, indicating a strong correlation between CAI and NPR. The exponential regression equation with a high negative index means that the decline in NPR is steep with respect to CAI. The effect of CAI on the PR of the surface miner is twofold. As the CAI of the rockmass increases, the picks of the surface miner rapidly wear out. This requires frequent replacement of the picks, resulting in delays in the surface miner's operation, which causes a reduction in the NPR. Furthermore, until the picks are replaced, the surface miner with worn-out picks requires more time to cut the rock mass. This also reduces the NPR. Origliasso et al. (2014) conducted an extensive investigation into the effect of the CAI on the production rate of a surface miner. They reported that there is an exponential decay relation between the index and the PR. They proposed a relation between the abrasion index and the PR as follows.

$$PR = \left(1 - \frac{CAI}{100}\right) * k * M_c$$

Where PR is the rate of production, CAI is the Cercher abrasivity index, k is a constant based on the site, and Mc is the rated capacity of the machine.

It is evident that as CAI increases, PR decreases, as the other two terms remain constant for a given machine and site.

It is seen from Figure 7 that the regression coefficient is high, indicating a strong correlation between E and NPR. The logarithmic regression suggests that the decline in NPR is initially steep, and the rate of decrease reduces with increasing values of Young's modulus. E varies inversely with crack density (Kulhawy, 1975; Segall, 1984; Walsh, 1965). This indicates that as the E increases, the crack density in the rockmass reduces. This also means that the rockmass with a high E is more resistant to deformation and fracture than the rockmass with a small Young's modulus. As the resistance to deformation increases, the surface miner must reduce the cutting speed to cut the given rock mass, which translates into a low NPR.

(Prakash et al., 2015) have also reported similar results. They have found that the fracture toughness of a rockmass is in direct proportion to the Young's modulus. This adversely affects the performance of the surface miner, thereby reducing the NPR. It is seen from Figure 8 that there is a correlation between IV_P and NPR, which is evident from a high value of the regression coefficient. The logarithmic regression implies that the decline in NPR is initially steep, and the rate of decrease diminishes as the IV_P values increase. The value of IV_P indicates the overall condition of a rockmass.

The IV_P in a fractured rockmass is less than that in an intact rockmass. When the fracture density of a rockmass reduces, the rockmass becomes more difficult to cut. The difficulty in cutting is associated with the requirement of more force to fracture and remove the material. This results in slower cutting speeds, as the machine must exert more effort to break through the rock. The slower cutting speed indicates that the surface miner requires more time to cut the rock mass, ultimately leading to a decrease in production rate.

7. Bivariate Regression of PCM

Graphs have been plotted with each of the geotechnical parameters as an independent variable and the PCM as a dependent variable. The bivariate regression equations have been obtained along with the Coefficient of determination (R2). The Analysis of the PCM vis-à-vis the geotechnical parameters are presented in Figures 9 to 12.

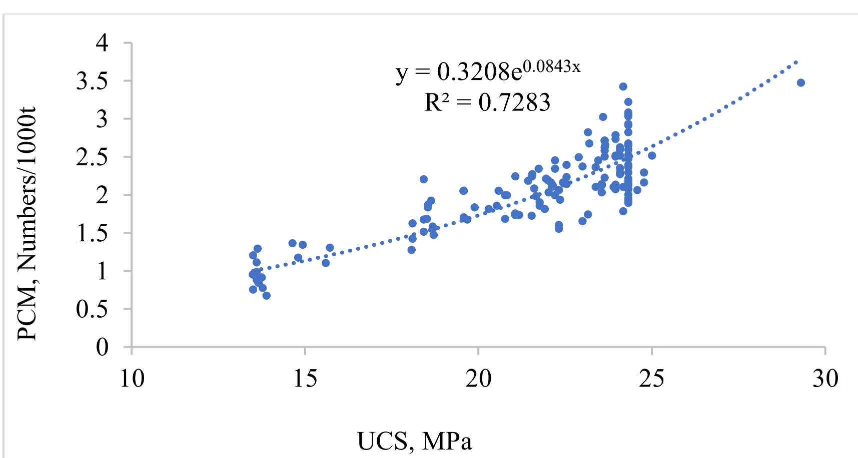

Fig. 1. Regression of PCM on UCS

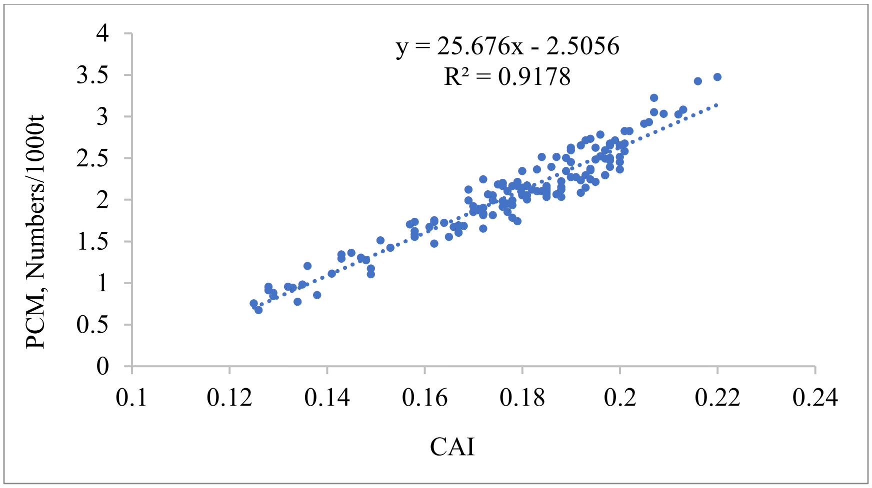

Fig. 10 Regression of PCM on CAI

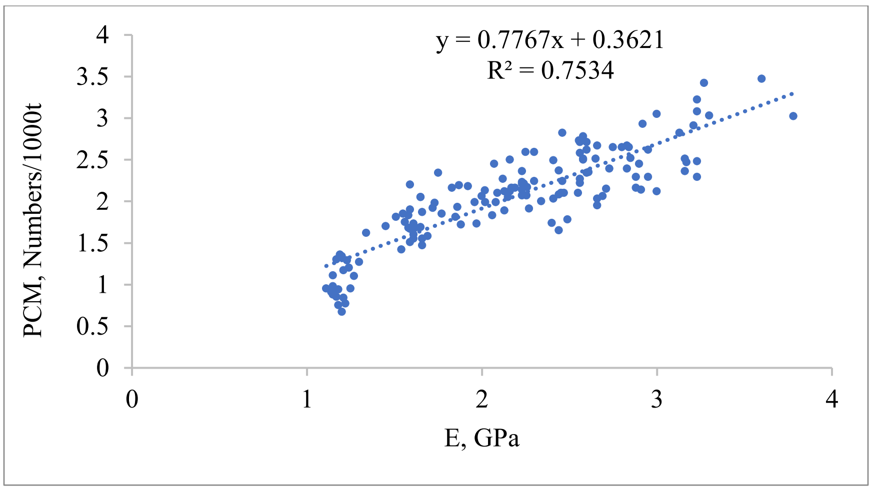

Fig. 11 Regression of PCM on E

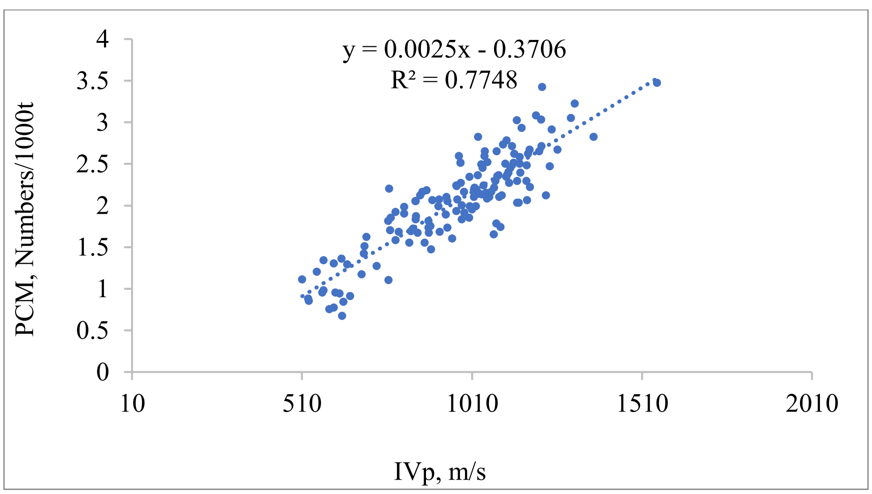

Fig. 12 Regression of PCM on IV_p

Figure 9 illustrates that the regression coefficient is 0.8. In rock engineering, a regression coefficient above 0.8 is considered satisfactory, taking into account localised geotechnical variation (Dhekne et al., 2017). Therefore, the value of R^2 obtained in the Bivariate regression analysis is acceptable. It is also evident that a slightly lower R^2 is due to variation in pick consumption in a rock mass with a UCS of 24.33 MPa. The UCS of coal and host strata is an important mechanical property that affects the performance and wear rate of cutting tools in surface mining operations. UCS The maximum axial stress a material can withstand before failure is represented by UCS, and the rock cuttability is primarily determined by UCS. The energy required for the initiation and propagation of the fractures in the rockmass increases with the UCS of the rockmass. This leads to an increase in the requirement of cutting force because of the excellent resistance at the tool-rock interface. Subsequently, while cutting a high-UCS rockmass, the pick consumption increases due to increased mechanical loading, higher temperatures at the cutting edge, and more intense abrasive interactions. (Bilgin et al., 2006). An increase in the cutting force causes an increase in the loading at the tip of the cutting pick. With an increase in the cutting force, the loading at the pick tip also increases.

Figure 10 exhibits a high regression coefficient, indicating a strong correlation between CAI and PCM. The linear regression shows that PCM increases steadily as its values rise. As the CAI increases, the percentage of quartz also increases. Quartz is considered a highly abrasive material due to its high compressive strength and has angular crystals. The high quartz content and angular grain structure in dirt bands can lead to micro-fracturing, chipping, and eventual failure of the carbide insert of the pick. In addition, the cyclic impact loads and thermal stresses generated during repeated transitions between coal and dirt bands exacerbate fatigue and wear at the tool-rock interface.

In Figure 11, it is observed that the R-squared value is 0.7534, which is considered to be satisfactory. It is observed that a marginally low value of R^2 is due to the different values of pick consumption in the rockmass, which has a modulus of elasticity of around 1.17 GPa, 1.60 GPa, and 2.60 GPa. The overall trend indicates that the PCM increases with UCS. Higher Young's modulus in coal typically results in elevated pick wear due to increased brittleness and higher stress concentrations at the tool-rock interface. The rapid fracture of brittle coal can generate sharp-edged fragments that increase the abrasivity at the cutting interface, accelerating the wear of tungsten carbide inserts. Moreover, cutting through rigid coal generates higher dynamic forces and vibrations, which may contribute to chipping, spalling, or even premature failure of picks. Conversely, softer coal (characterised by a lower E) tends to result in smoother tool engagement but higher specific energy consumption due to greater plastic deformation and less efficient crack formation (N. P. Singh et al., 2017).

Experimental studies and field investigations have shown a correlation between coal stiffness and pick consumption rates. (Tiryaki & Dikmen, 2006) Observed that as the Young's modulus of coal increases, there is a corresponding rise in instantaneous cutting forces and pick consumption, particularly in surface miners operating under continuous cutting conditions. This implies that in high-modulus coal seams, picks undergo increased mechanical and thermal stresses, necessitating more frequent replacement and resulting in higher operational costs.

As shown in Figure 12, R^2 is 0.7748. The R-squared value is considered satisfactory. The overall trend indicates that the PCM increases with IV_P. P-wave velocity is a measure of heterogeneity within coal seams, especially in the presence of dirt bands, which often exhibit higher velocities than coal itself. (Goktan & Gunes, 2005) noted that sudden transitions in P-wave velocity within a seam correspond to changes in lithological hardness, which in turn significantly affect pick life. Picks entering high-velocity zones from lower-strength coal formations experience impact loading due to abrupt changes in material properties, resulting in increased stress on the picks. The pick stress accelerates the pick wear, causing an increased consumption of the picks.

8. Conclusion

There is a considerable increase in the number of surface miners employed in the opencast mines to mitigate the dangers due to blasting to the people residing in the vicinity of the mines. Considering the importance of the geotechnical parameters in cutting the rockmass by the surface miners, an investigation has been conducted.

The bivariate regression analyses between the dependent variables (NPR and PCM) and the selected geotechnical parameters (UCS, CAI, E, and IVP) reveal clear trends in their interrelationships. Based on the Coefficient of Determination (R^2) values, the Cerchar Abrasivity Index (CAI) shows the strongest correlation with both NPR and PCM. For NPR, CAI exhibits the highest R^2 value (0.91), indicating that abrasivity exerts a dominant influence on productivity decline.

The Uniaxial Compressive Strength (UCS) follows with an R^2 value of 0.88, confirming that higher rock strength significantly reduces NPR due to increased cutting resistance. The Intactness or P-wave Velocity (IVP) demonstrates the next level of influence with R^2=0.85, implying that rock mass integrity substantially affects production, but to a lesser degree. The Young's Modulus (E) records the lowest, though still meaningful, R^2 value (0.82), suggesting its secondary role in governing deformability-related cutting behaviour.

In the case of PCM, the CAI again shows the highest R^2 value (0.89), followed by UCS (0.80), IVP (0.77), and E (0.75). This sequence confirms that abrasivity primarily governs pick consumption due to its direct control over wear mechanisms. At the same time, UCS and IVP have secondary but appreciable effects through mechanical loading and heterogeneity. The relatively lower contribution of E indicates that stiffness influences wear indirectly by affecting brittleness and fracture propagation during cutting.

Overall, CAI emerges as the most critical parameter influencing both NPR and PCM, followed by UCS, IVP, and E, respectively. Recognising the hierarchy of these relationships allows for more reliable prediction of surface miner performance, facilitating machine selection, cutting parameter optimisation, and cost-effective production planning. This integrated understanding of geotechnical and mechanical interactions forms a rational basis for improving operational efficiency and sustainability in surface mining.

Author Contribution Statement

OPS - Data collection, Analysis, and Manuscript preparation; PYD - Conceptualisation, Manuscript review, and editing; MP - Manuscript review and editing.

Acknowledgements

The authors acknowledge the support and facilities provided by the Department of Mining Engineering, National Institute of Technology Raipur, India.

References

[1] Hemant Agrawal, and A.K. Mishra, "Evaluation of Initiating System by Measurement of Seismic Energy Dissipation in Surface Blasting," *Arabian Journal of Geosciences*, vol. 11, no. 13, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[2] Prakash Amar, Murthy Vemavarapu Mallika Sita Ramachandra, and Singh Kalendra Bahadur, "Performance Simulaton of Surface Miners with Varied Machine Parameters and Rock Conditions: Some Investigations," *Journal of Geology and Mining Research*, vol. 5, no. 1, pp. 12-22, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[3] Rajesh Bhatta, Nilima Dash, and Bibhuranjan Nayak, "Characters of Liptinites in Different Seams of Talcher Coalfield, Odisha, India," *Journal of the Geological Society of India*, vol. 98, no. 2, pp. 193-197, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Nuh Bilgin et al., "Dominant Rock Properties Affecting the Performance of Conical Picks and the Comparison of Some Experimental and Theoretical Results," *International Journal of Rock Mechanics and Mining Sciences*, vol. 43, no. 1, pp. 139-156, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[5] K. Dey, and A.K. Ghose, "Selecting a Surface Miner - An Algorithm," *Journal of Mines, Metals and Fuels*, vol. 57, no. 9, pp. 282-287, 2009. [Google Scholar]

[6] K. Dey, and P. Sen, "Continuous Surface Miner in Mining Limestone and Coal in India - A Comparative Study," *Journal of Mines, Metals and Fuels*, vol. 56, no. ¾, pp. 51-54, 2008. [Google Scholar] [Publisher Link]

[7] A.K. Ghose, "Surface Miner Operations at Lakhanpur Opencast Project: A Preliminary Evaluation," *International Seminar on "Quality, Productivity and Environment-the Challenges"*, Bhubaneswar, IMMA, 2000. [Google Scholar]

[8] R.M. Goktan, and N. Gunes, "A Comparative Study of Schmidt Hammer Testing Procedures with Reference to Rock Cutting Machine Performance Prediction," *International Journal of Rock Mechanics and Mining Sciences*, vol. 42, no 3, pp. 466-472, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[9] Shrikant M. Harle, and Rajan L. Wankhade, "Machine Learning Techniques for Predictive Modelling in Geotechnical Engineering: A Succinct Review," *Discover Civil Engineering*, vol. 2, no. 1, pp. 1-21, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] I.O. Jones, and S. Kramadibrata, "An Excavating Power Model for Continuous Surface Miners," *AusIMM Proceedings*, vol. 300, no. 2, pp. 33-39, 1995. [Google Scholar] [Publisher Link]

[11] Sarma S. Kanchibotla, and Andrew Scott, "A Study of the Influence of Buffering on Coal Edge Loss and Dilution from Cast Blasting," *Fragblast*, vol. 3, no. 4, pp. 365-375, 1999. [CrossRef] [Google Scholar] [Publisher Link]

[12] E.A. Khoyutanov, and V.L. Gavrilov, "Coal Quality Control in Mining Complex-Structure Deposits," *Journal of Mining Science*, vol. 55, no. 3, pp. 399-406, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[13] M. Kiani et al., "Risk Assessment of Blasting Operations in Open Pit Mines using FAHP Method," *Mining of Mineral Deposits*, vol. 13, no. 3, pp. 76-86, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[14] Suseno Kramadibrata, *The Influence of Rock Mass and Intact Rock Properties on the Design of Surface Mines with Particular Reference to the Excavation of Rock, Part-I, II and III*, School of Civil Engineering, Curtin University of Technology, 1996. [Google Scholar] [Publisher Link]

[15] Fred H. Kulhawy, "Stress Deformation Properties of Rock and Rock Discontinuities," *Engineering Geology*, vol. 9, no. 4, pp. 327-350, 1975. [CrossRef] [Google Scholar] [Publisher Link]

[16] Romil Mishra, Arvind Kumar Mishra, and Bhanwar Singh Choudhary, "High-Speed Motion Analysis-Based Machine Learning Models for Prediction and Simulation of Flyrock in Surface Mines," *Applied Sciences*, vol. 13, no. 17, pp. 1-33, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] V.M.S.R. Murthy et al., "Development of a Cuttability Index of Surface Miner for Performance Prediction in Different Geomining Conditions," *International Symposium on Rock Mechanics and Geo-Environment in Mining and Allied Industries*, Banaras Hindu University, Varanasi, pp. 12-14, 2009. [Google Scholar] [Publisher Link]

[18] Chiara Origliasso, Marilena Cardu, and Vladislav Kecojevic, "Surface Miners: Evaluation of the Production Rate and Cutting Performance Based on Rock Properties and Specific Energy," *Rock Mechanics and Rock Engineering*, vol. 47, no. 2, pp. 757-770, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[19] José Padarian, Budiman Minasny, and Alex B. McBratney, "Machine Learning and Soil Sciences: A Review Aided by Machine Learning Tools," *Soil*, vol. 6, no. 1, pp. 35-52, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[20] Katarzyna Pentoś et al., "Evaluation of Multiple Linear Regression and Machine Learning Approaches to Predict Soil Compaction and Shear Stress based on Electrical Parameters," *Applied Sciences*, vol. 12, no. 17, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] G.K. Pradhan, Om Prakash, and N.R. Thote, "Blast Free Mining in Indian Surface Coal Mines-Current Trend," *Mine Planning and Equipment Selection: Proceedings of the 22nd MPES Conference, Dresden, Germany, 14th - 19th October 2013*, pp. 335-357, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[22] A. Prakash, and V.M.S.R. Murthy, "Hierarchy of Parameters Influencing Cutting Performance of Surface Miner through Artificial Intelligence and Statistical Methods," *Current Science*, vol. 112, no. 6, pp. 1242-1249, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[23] Amar Prakash, and Vemavarapu M.S.R. Murthy, "Prediction of Cutting Speed of Surface Miner for Coal and Limestone Production under Varied Rock Mass Conditions," *Journal of the Geological Society of India*, vol. 100, no. 8, pp. 1122-1128, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] A. Prakash, V.M.S.R. Murthy, and K.B. Singh, "Chip Size Characterization for Selecting Optimum Production Parameters of Surface Miner Operating in a Coal Mine," *Current Science*, vol. 108, no. 3, pp. 422-426, 2015. [Google Scholar] [Publisher Link]

[25] Lvinash Prasad, Sandeep Prasad, and G.K. Pradhan, "Performance Appraisal of Surface Miner in Opencast Mines: A Case Study," *The Indiln Mining and Engineering Journll*. [Google Scholar]

[26] Paul Segall, "Rate-Dependent Extensional Deformation Resulting from Crack Growth in Rock," *Journal of Geophysical Research: Solid Earth*, vol. 89, no. B6, pp. 4185-4195, 1984. [CrossRef] [Google Scholar] [Publisher Link]

[27] Alokranjan Senapaty, and P. Behera, "Stratigraphic Control of Petrography and Chemical Composition of the Lower Gondwana Coals, Ib-Valley Coalfield, Odisha, India," *Journal of Geoscience and Environment Protection*, vol. 3, no. 4, pp. 56-66, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[28] A. Singh et al., "Failure Analysis and Performance Improvement using Surface Miner on Field Breakdown Data: A Case Study," *Industrial Engineering Journal*, vol. 12, no. 9, pp. 1-31, 2019. [Google Scholar]

[29] Nilesh P. Singh, Aarif Jama, and Nawal Kishore. "Impact of Coal Quality on Longevity of Picks of Surface Miner-A Case Study," *International Conference on Deep Excavation, Energy Resources and Production*, Varanasi, India, vol. 170, 2017. [Google Scholar]

[30] Nilesh Pratap Singh et al., "Impact of Surface Miner Utilisation on Production Efficiency in Opencast Coal Mines Using Least Squares Method: A Case Study," *Journal of The Institution of Engineers (India): Series D*, vol. 105, no. 1, pp. 567-580, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[31] B. Tiryaki, and A. Cagatay Dikmen, "Effects of Rock Properties on Specific Cutting Energy in Linear Cutting of Sandstones by Picks," *Rock Mechanics and Rock Engineering*, vol. 39, no. 2, pp. 89-120, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[32] Ashish Kumar Vishwakarma et al., "Investigations on the Influence of Applied Thrust on Rock Penetration Rate by a Raise Boring Machine Using Numerical Simulation and Experimental Trials," *Mining, Metallurgy and Exploration*, vol. 40, no. 4, pp. 1187-1197, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] J.B. Walsh, "The Effect of Cracks on the Compressibility of Rock," *Journal of Geophysical Research*, vol. 70, no. 2, pp. 381-389, 1965. [CrossRef] [Google Scholar] [Publisher Link]

[34] Thomas Welchowski et al., "Techniques to Improve Ecological Interpretability of Black-Box Machine Learning Models: Case Study on Biological Health of Streams in the United States with Gradient Boosted Trees," *Journal of Agricultural, Biological, and Environmental Statistics*, vol. 27, no. 1, pp. 175-197, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[35] Manish Yadav et al., *Surface Miner: A Green Approach to Coal Production in Indian Surface Coal Mines*, Green Innovation, Sustainable Development, and Circular Economy, CRC Press, 1st ed., pp. 17-32, 2020. [Google Scholar] [Publisher Link]