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Assessing excavatability in varied rock mass conditions using real-time data and machine-learning technique

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ABSTRACT

This study investigates shovel excavation performance across various rockmass conditions by integrating real-time performance assessments, rockmass property analysis, and machine learning techniques. The Excavatability of rock masses under varied conditions, including variations in sediment types (e.g., sand, silt, clay), geological structure, and physical properties such as moisture content and density. Correlation analysis revealed significant positive relationships between Total Loading Time (TLT) and selected rock properties, specifically uniaxial compressive strength (UCS), tensile strength (TS) cohesion (C), and moisture content (M), and a negative correlation was observed with wet bulk density (WBD). Pareto analysis further highlighted C, UCS, and TS as the most impactful factors, cumulatively accounting for 56% of the total effect on excavation performance. A multiple linear regression model, using TLT as the dependent variable and significant rock properties (C, UCS, M) as predictors, achieved a strong correlation (R=0.76) and explained 76% of the variance, demonstrating the model's effectiveness in estimating shovel performance. K-nearest neighbors (KNN) classification, optimized with a k-value of 7 and Manhattan distance, achieved a high accuracy of 99.43% in categorizing the excavation difficulty into four distinct classes. The frequency distribution of TLT data indicates that most materials in the pit are categorized under the "Very Easy" and "Easy" classes, simplifying excavation processes. This research underscores the importance of the key rock properties in evaluating the excavation performance predictions and supporting optimized operational strategies in mining. Future work could expand on these findings by using additional machine-learning techniques and exploring non-linear models to capture complex relationships.

1. Introduction

Global trends in economics, technical, and geopolitical developments are driving higher demand for minerals, influencing mining operations [1]. Surface mining, particularly open-pit mining, is favored for its higher production rates and simpler operational processes as compared to underground techniques [2]. Open pit mining is a commonly practiced surface exploitation technique, which involves the construction of benches (or levels) within the earth's crust to uncover the targeted mineral, and subsequently excavate it [3]. The unit operations in open pit mining involve three key operations, i.e., removal of overburden, extraction of the mineral, and transportation of overburden and mineral to their respective destination. Heavy excavation equipment such as draglines, hydraulic excavators, and bucket wheel excavators (BWEs) are vital to the process, and their effective utilization is critical to minimizing costs and optimizing production. Utilization of equipment, especially hydraulic shovels, is influenced by the geological and geomechanical characteristics of the rockmass. Equipment performance can be affected by the heterogeneity of the lithology, where different rock types and properties exist at varying pit levels. To optimize shovel usage, variability in the rockmass properties needs to be addressed. This variability, in turn, impacts loading times and the performance of the shovel at different pit levels [4]. A substantial capital investment is made in the procurement of mining equipment. Hence, the effective utilization of the equipment is one of the main economic considerations in every surface mining project [5, 6].

Equipment utilization indicates how effectively it is deployed and its contribution to overburden removal and the excavation of minerals [7]. The rockmass behavior significantly affects the excavation performance of mining equipment. The deployment of equipment must consider the geological and geomechanical characteristics of the rockmass to meet production requirements at each bench and simultaneously maintain the overall slope of the pit [8]. Excavators, notably hydraulic shovels, have gained widespread popularity due to their variety in terms of scale of operation, especially when used for excavating soft sedimentary rocks. Hydraulic-operated shovels are now commonly employed in mining and civil worksites, playing a crucial role in both, the drill-blast excavation, and the mechanical excavation methods [9]. The optimization of shovel utilization is contingent upon correlating the variability in rock mass properties with its performance parameters. This variation needs to be addressed by considering the lithological heterogeneity. Lithological heterogeneity is the variation in the rock mass properties at different working levels of the pit. The material being excavated and loaded by the shovel may vary from sandy, unconsolidated mass to soundly compacted rock mass. Additionally, high-strength rock layers may be interbedded with lower-strength layers, or vice versa. In either case, the excavation performance of the hydraulic shovel significantly varies. Therefore, the shovels working at various levels will take different loading times to excavate the material from the bench face and load it into the truck.

Excavatability is a critical concept in mining and geotechnical engineering, which relates to how easily soil or rock can be dug up using excavation machinery, such as hydraulic shovels or other earth-moving equipment. It plays a key role in the efficiency, costs, and safety of excavation projects, particularly in the mining industry. The key aspects of excavatability include rockmass parameters and operational parameters for a shovel-truck mining system (Fig. 1). The Rockmass parameters include the mechanical, physical, and structural properties of rock. Literature indicates that the mechanical or strength properties are of particular importance while assessing excavatability. For a Shovel-truck mining system, the operational parameters include the shovel cycle time, the number of cycles to fill one truck, and the bucket fill factor. Considering excavation characteristics of rock mass is a primary aspect of mine planning and accomplishment of production targets safely, effectively, and economically. The excavatability of any given rock mass depends on rock mass parameters such as its mechanical, physical, and structural properties, which in turn affect the operational parameters of the mining equipment. On the other hand, it also impacts the optimum utilization of mining equipment and increases the risk of equipment breakdowns.

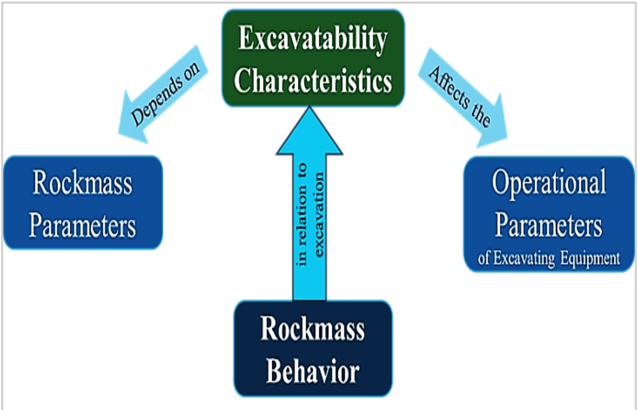

Fig. 1. Conceptualization Of Excavatability Characteristics

Studies have shown that the specific cutting energy (SCE) as determined by cutting test/cutting resistance developed by Orenstein and Koppel (O and K) is also used to classify the rock mass excavatability. Such classifications are useful in determining the excavation performance in varying rock types [10]. Physical characteristics of rocks including hardness, density, moisture, grain size, and fragment profile also affect the ease of excavation of rock mass significantly [11]. The bucket fill factor is also a principal factor in assessing the excavatability. The bucket fill factor is the actual filling of the equipment bucket compared to the theoretical capacity of the bucket described by the manufacturer. This factor significantly affects the excavation efficiency. Therefore, the assessment of excavatability requires integration of the physical properties of rock mass and their effect on the bucket fill factor. This integration provides more accurate estimates of the excavation performance. Empirical methods such as the classification systems developed to classify the rockmass are used to assess the excavation potential of mining equipment, considering the geotechnical characteristics of the rockmass [12]. Multiple factors such as the uniaxial compressive strength (UCS) of rock, its weathering profile, discontinuity profile, and geological contact (unconformity) profile are considered while assessing the excavation capability of equipment. In this context, Scoble and Muftuoglu developed an index to represent the diggability of rockmass based on geotechnical parameters [9]. Additionally, an excavation rating system based on compressive strength, hardness, spacing of discontinuities, weathering, and seismic velocity was proposed [13]. However, their proposed diggability index does not considers the moisture content of the rocks and fails to classify rocks with exceptionally low UCS.

Excavation performance is measured utilizing parameters including the rate of digging, payload frequency, and shovel productivity. Among these, the rate of digging is considered the most influential factor [14]. It describes the ratio of payload to dig time, indicating the importance of dig time in determining the overall cycle time of excavators. Dig time is a primary component of material handling in mining operations, accounting for approximately half of the total cycle time [15]. The time taken by an equipment to excavate a particular volume of rock, and fill the bucket is called the dig time or excavation time. It does not include the swing time of the excavator boom towards the dump truck (to empty the load carried in a bucket) and back swing time (required to return to face for the next excavation cycle) [16]. This is because swing times have no relevance in determining the excavation performance of the equipment.

Studies have also been conducted assessing the relationship between excavation easements and the productivity of shovels. In this context, Manyele investigated the excavation performance of the shovel and concluded that the cycle time of the shovel is the most critical parameter for performance assessment [17]. This research also considers various other parameters including the excavator type, location of operation, and productivity achieved. Additionally, another study was performed integrating the use of open-pit and underground mining technology, to increase the effectiveness of resource extraction [18]. This combination leads to enhanced productivity of the shovel. The application of queuing theory in shovel-truck system optimization has been practiced in recent years. Research on sustainable haulage operations in an open pit phosphate mine was conducted, considering the variations in truck fleet size and their effect on truck waiting times in queue, and shovel productivity [19]. This study extended significant contributions toward the applications of queuing techniques to optimize the effectiveness of shovel-truck mining operations. In addition, Elijah et al. developed a queuing model and optimized the material haulage operations, highlighting the relationship between waiting times and shovel utilization [20].

The influence of technology and modernization in shovel-truck systems cannot be ignored. A recent study focused on electrification alternatives for mine transportation systems, to optimize productivity, and contribute to sustainability in mining activities. The evolution to electrified transportation systems offers a flexible and more adaptable solution, to achieve targeted demand, thus enhancing the overall productivity of shovels [21]. Machine learning (ML) algorithms have also gained prevalent popularity for their applications in the analysis of geological data and estimation of rock mass behavior. Several studies have highlighted the application of different ML models, including random forest (RF) and support vector machine (SVM) in estimating the occurrence of landslides based on geological conditions [22]. These algorithms are also applicable to predict excavatability by considering rock mass parameters such as type of rock, discontinuity orientation, and moisture content, all of which affect the ease of excavation. Additionally, the applications of real-time data acquisition using different sensors increase the predictive accuracy of these models and dynamically adjusts the decision-making process accordingly. The significance of real-time data in determining rockmass characteristics cannot be neglected. The application of Internet of Things (IoT) technology has proven particularly useful for geotechnical engineers in acquiring continuous data on rock mass properties, which are further assessed through various ML algorithms for the prediction of excavatability. These techniques not only account for reliability in decision-making but also provide faster processing of outputs for excavation operations. Integration of real-time rockmass monitoring systems using ML techniques also assists in identifying the possible hazards before the occurrence of an accident, as a result improving the cost-effectiveness and downtimes associated with geological uncertainty [23, 24].

In conclusion, the reviewed literature indicates that excavatability assessment is crucial for the optimum utilization of shovel and overall productivity of open-pit mining operations. Considering critical factors including rockmass properties (mechanical, physical, and structural), and performance parameters of the mining equipment will significantly increase the efficiency of excavation operations, minimize the operational expenses, and improve overall productivity. Advanced ML techniques, empirical equations for classification, and accurate consideration of equipment-rock mass interaction provide better performance predictions, eventually leading toward proper equipment selection, deployment, and decision-making agenda. Additionally, the combination of machine learning techniques and real-time data acquisition provides a reliable method of assessing excavatability in different rock mass conditions, thus proving to be a useful optimization tool.

The lithology of the Thar coalfield is comprised of three different geomaterials, including top stratum Dune Sand, poorly consolidated alluvium, and loosely consolidated rocks of sedimentary origin. The coal seams of lignite origin lie in the geological formation identified as the Bara Formation. The sedimentary rocks hosting the coal seams exhibit very low UCS values, hence characterized as "soft sedimentary rocks" [25]. The excavatability classifications previously developed fail to indicate the excavatability behavior of Thar coalfield. Therefore, to address this gap, this research aims to determine the rockmass parameters that affect the excavation performance of hydraulic shovels and develop a classification based on excavation performance in soft sedimentary rocks at Thar Coalfield, using the KNN algorithm. This approach facilitates the real-time decision making for equipment selection and deployment. The formation characteristics such as unconfined compressive strength, ultimate tensile strength, cohesion, internal friction angle, density, rock quality designation, and moisture content were determined for each rock and soil layer. Based on the shovel performance in various rock and soil layers, an excavatability classification is proposed in this study.

2. Study Area Description

The Thar coalfield is situated in the Thar desert of Sindh province of Pakistan. It has about 175 billion tons of lignite coal making it one of the largest coal deposits in the world. Thar coal is currently the most essential and sustainable energy source of Pakistan. The discovery of coalfield dates back to late 1980's, however the resources were confirmed through a detailed exploration of the area in 1994 [26].

The coalfield is divided into 13 blocks numbered in roman as per their exploration sequence. Fig. 2 presents the layout of the Thar coalfield area [27]. The Thar coal project is currently the major coal producing project in Pakistan, which is focused on the utilization of Indigenous coal reserves for electricity generation.

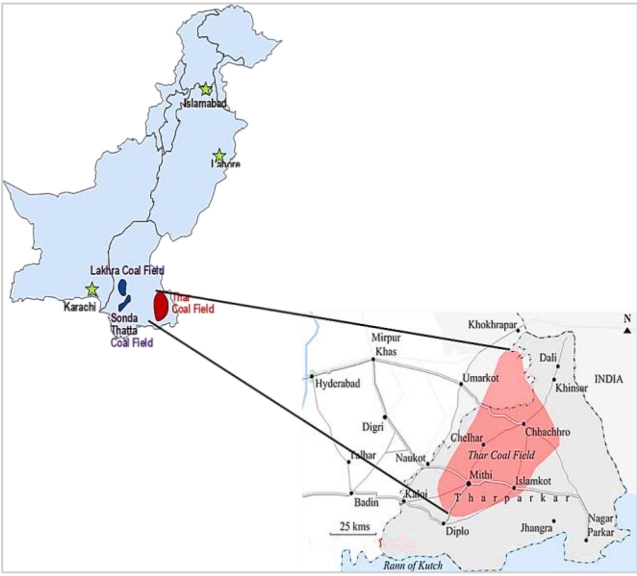

Fig. 2. Location Of The Study Area

The Thar coalfield is comprised of three geological formations [28]. The top surface of the coalfield is composed of undulating and thick dunes of Recent formation deposited during the Quaternary period. Lithologically, the Recent formation is composed of a blend of sand, silt, and clay [2]. The Subrecent Formation underlying the Recent Formation, also deposited during the same period. These are alluvial deposits consisting of silty sand, sandstone, siltstone, and claystone. Finally, meets the Bara Formation which contains the coal seams, deposited during the Tertiary period of the Cenozoic era. The coal-bearing formation consisted of a sequence of coal seams of varying thickness, deposited at about 130 meters and 250 meters deep, with a cumulative seam thickness of 1.45 – 42.6 meters [29].

This entire stratum is slightly dipping at about 2º, which makes it structurally simple, and no major fault zones are encountered within the coalfield. The Bara formation rests upon the major unconformity, underlain by the granite basement zone deposited during the Precambrian era [30]. Due to a long and consistent period of erosion and non-deposition, the basement granite is highly weathered, medium compact composed of coarse to fine quartz grains, and a small deposit of rhyolite and diorite. Fig. 3 presents the generalized lithology and stratigraphy of the Thar coal basin.

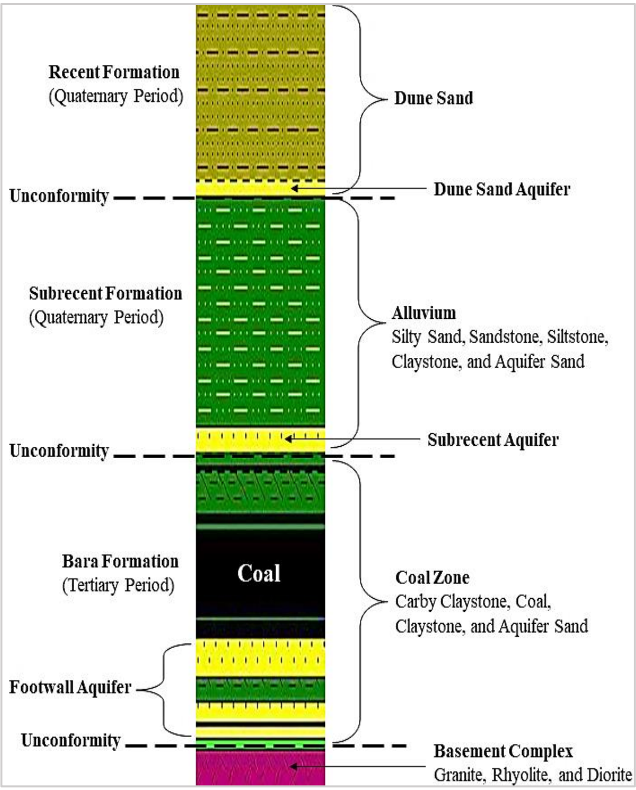

Fig. 3. Generalized Lithology and Stratigraphy Of Coal Basin

At the base of the Recent formation lies the dune sand aquifer. This aquifer is present all over the Thar desert and on the Indian side. The water column in this aquifer is only around one to five meters at maximum. Near the base of the Subrecent Formation, the Subrecent aquifer is located, which is widely spread over the entire Thar area. This aquifer is 0 to 12 meters in thickness with an average thickness of six meters. The bottom aquifer, also known as the footwall aquifer, is present at the base of the Bara formation, also extending the overall coalfield area, with a variable thickness ranging between 30 to 50 meters.

3. Methodology

3.1 Data Collection

The study involves extensive data collection through real-time on-site investigations focusing on the excavation operations and performance of shovels in varying lithological units of the open pit mine. The shovels considered in this study are backhoe-type hydraulic-operated having a bucket capacity of seven cubic meters (heaped). These shovels were loading two different variants of trucks, i.e., for overburden and coal. The trucks used to carry overburden loads to dumpsites are thirty-four cubic meter capacity trucks, whereas the trucks used to transport excavated coal to the crushing plant are fifty-four cubic meters. The difference in truck capacity is justified by matching their load (tonnage) capacity, because the Coal is less dense as compared to the overburden and inter-burden rock/soil material.

The data collection methodology involved the recording of videos of shovels' excavation operations. The key performance parameters of the shovel are then extracted from these videos, including shovel cycle time (SCT), number of cycles (N) to fill a truck, total loading time (TLT), and bucket fill factor (BFF). The performance parameters are then correlated with major rock mass properties such as uniaxial compressive strength (UCS) in MPa, tensile strength (TS) in MPa, cohesion (C) in kPa, internal friction angle (ϕ) in degrees, moisture content (M) in %, wet bulk density (WBD) in tons/m3, and rock quality designation (RQD) in %. These rock properties were acquired from previous studies comprising the in-situ and laboratory investigations [25, 31]. The laboratory tests were conducted following standardized procedures outlined in American Society for Testing and Materials (ASTM) and International Society for Rock Mechanics (ISRM) guidelines, to ensure reliability, and accuracy of the input parameters [32-34]. This data collection methodology integrates the geotechnical and operational parameters, to gain a clear understanding of how the rock mass properties affect the excavation performance of the shovel [1]. The performance of shovels at various rock and soil layers is analyzed, each showing different excavatability behavior. The variation in rock properties showed a considerable impact on the operational effectiveness of the shovel. The Total Loading Time (TLT) is considered a major performance indicator in this study.

3.2 Nomenclature Of The Operational Parameters For Excavatability Assessment

This section presents the description of the operational parameters extracted from the videos. Each parameter is defined with a notation and unit of measure.

- Truck Capacity (Ctruck), m3 – The Total volume of material that can be filled in a truck.
- Bucket Capacity (Cbucket), m3 – The Total volume of material that can be filled in a Shovel Bucket.
- Number of Cycles (N) – The total number of loading cycles a shovel takes to fill one truck.
- Shovel Cycle Time (SCT), sec. – The time taken by a shovel to load one bucket, swing towards the truck position, empty the bucket

in the truck, and swing back to a position for the next loading.

- Spotting Time (Tspot), sec. – The time taken by a truck to spot itself at the loading position.
- Leaving Time (Tleave), sec. – The time taken by a truck to leave the loading spot.
- Bucket Fill Factor (BFF), % – The percentage of available volume in an excavator bucket that is filled.
- Total Loading Time of Truck (TLT), sec. – The total time a Shovel takes to fill one truck including its spotting and leaving times at the loading point. The spotting and leaving times of trucks are included in the TLT because the shovel engages in the excavation work while the loaded truck departs from the loading spot and an empty truck gets positioned for loading. In this way, the TLT provides a comprehensive measure of the entire excavation and loading cycle.

The bucket fill factor and Total Loading Time were calculated using the following equations:

$$BFF = \frac{C_{truck}}{N \times C_{bucket}} \times 100 \qquad (1)$$

$$TLT = (SCT \times N) + T_{spot} + T_{leave} \qquad (2)$$

3.3 Correlation Of Rock Mass Properties With Total Loading Time (TLT)

The study investigates the relationship between total loading time (TLT) and rock mass properties across various working levels (benches) to evaluate the predictive significance of geotechnical parameters on excavatability. Linear multiple regression analysis is conducted to model the relationship between TLT and the corresponding rock properties at each working level. The proposed regression model is validated by comparing the predicted TLT, based on rock properties, with the actual shovel performance observed in the field. This accounts for the evaluation of the model's accuracy in the prediction of shovel performance and excavatability. Additionally, this study involves the application of the K-nearest Neighbors (KNN) classification algorithm to classify the strata into unique classes based on the predicted TLT data. These categories reflect various levels of excavatability, ranging from easy to difficult, based on the TLT predictions. Finally, an excavatability classification is proposed, which classifies various rock and soil layers into different classes, also describing the corresponding level of effort required to excavate the rock/soil material.

The comprehensive methodology used in this study includes the regression analysis, its statistical validation, and excavatability classification presented in Fig. 4.

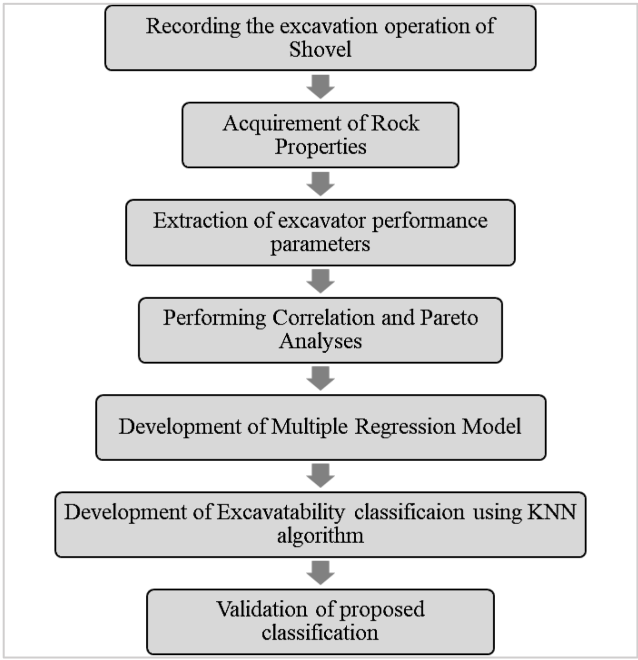

Fig. 4. Methodology Flowchart

4. Excavation Performance Assessment

The shovel operation data was acquired through real-time performance assessment by recording the videos of the excavation and loading operation for ten working shifts, equal to 80 working hours. A total of 40 shovels were recorded during the stated time duration, and the operational parameters such as, number of trucks, number of shovels, shovel cycle time, total loading time, and bucket fill factor were extracted from the recorded videos that are presented in Table 1, along with the respective rock mass properties.

A significant variation in the shovel operating parameters across different rock and soil layers was observed, as summarized in Fig. 5 (a-d).

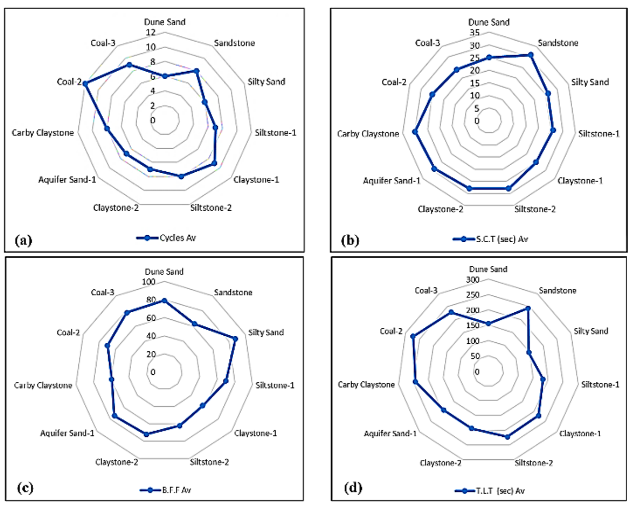

Fig. 5. Variation In Shovel Operational Parameters

Table 1

Rock mass properties of various lithological units and corresponding excavatability parameters

Rock type	Formation	Thickness (m)	No. of Trucks	N	SCT (sec)	TLT (sec)	BFF (%)	UCS (MPa)	TS (MPa)	C (kPa)	ϕ (deg.)	M (%)	WBD (t/m3)	RQD (%)
Dune Sand	Recent	40	13	6	25	178	79	0	0	51.3	38	20.2	2	0
Sandstone	Sub-Recent	12	12	8	31	260	65	2	0.27	79	42	21.8	2.04	53.7
Silty Sand	Sub-Recent	10	14	6	26	162	89	0.47	0.06	67.25	40	17.5	2.06	45.2
Siltstone-1	Sub-Recent	23	16	7	26	207	70	0.8	0.16	104	36	16.6	2.1	81.1
Claystone-1	Sub-Recent	15	15	9	25	241	57	0.6	0.15	148.2	35	18	2.15	79.3
Siltstone-2	Sub-Recent	10	14	8	28	252	62	0.66	0.08	126.1	31	13.5	2.2	81.6
Claystone-2	Sub-Recent	14	17	7	28	216	73	1.17	0.17	92	36	12.2	2.3	73.8
Aquifer Sand-1	Bara	15	13	7	29	228	73	0.5	0.07	108	41	21.2	1.99	0
Carby Clayston	Bara	10	6	8	30	279	62	1.3	0.24	191	39	35.6	1.57	75.5
Coal-1	Bara	23	8	12	25	307	67	1.87	0.22	235.4	45	46.8	1.29	89
Coal-2	Bara	10	6	10	24	255	83	1.81	0.21	188.4	48	40.6	1.26	84.6
Claystone-3	Bara	PIT BOTTOM												

In Table 1, the UCS is described as uniaxial compressive strength, and defines the peak compressive load bearing capacity rocks. TS is the indirect tensile strength, defined as the maximum tensile load carrying capacity. C indicates cohesive strength due to internal bond between the material particles. In soil, cohesion is due to inter-particle forces, such as electrostatic attractions, cementation, and the interblended clay minerals or moisture. In rocks, cohesion results from mineral interlocking, cementation, and the intrinsic strength of the material. The internal friction angle (ϕ) is a fundamental geotechnical property indicating the shear strength of a rock or soil due to particle interlocking and friction. Moisture content (M) is the amount of water present within the pores of rocks and soil, usually expressed as a percentage of the material's dry weight. Wet bulk density (WBD) refers to the total mass of material (solid and water) per unit volume. RQD is the rock quality designation, a basic geological parameter indicating the percentage recovery of core pertaining to the presence of geological anomalies (faults, joints, and bedding planes).

The rock properties presented in Table 1 were compared with the respective TLT values by a correlation analysis to check the impact of individual rock properties on the excavatability. The results of the correlation analysis are presented in Fig. 6. From the correlation analysis it was observed that majority of the correlation coefficients lie between 0.5–1. This shows that there is a significant positive relationship between TLT and UCS, TS, C, M, and RQD. An inverse correlation was observed between the TLT and WBD. However, a correlation coefficient of 0.31 was obtained for TLT and ϕ, indicating a moderate relationship.

	TLT	UCS	TS	C	ϕ	M	WBD	RQD
TLT (sec)	1							
UCS (MPa)	0.74	1						
TS (MPa)	0.74	0.92	1					
C (kPa)	0.84	0.58	0.57	1				
ϕ (deg.)	0.31	0.61	0.41	0.41	1			
M (%)	0.68	0.64	0.52	0.82	0.79	1		
WBD (t/m3)	-0.60	-0.59	-0.45	-0.79	-0.81	-0.98	1	
RQD (%)	0.55	0.58	0.64	0.63	-0.03	0.29	-0.27	1

Fig. 6. Correlation Coefficients Of Various Parameters

Additionally, the Pareto analysis was performed to assess the significance or impact of each rock property on the excavation performance of the shovel. For this reason, the TLT was compared with rock properties and showed a strong correlation. Fig. 7 presents the Pareto chart showing the analysis results. It can be observed that cohesion has the highest impact (0.84), contributing to 20% of the total cumulative effect. This indicates that cohesion is the most significant rock property influencing excavation performance. The UCS has an impact of 0.75 and brings the cumulative percentage to 38%. It is the second most influential factor. Tensile strength has an impact of 0.74, bringing the cumulative to 56%, showing it is another crucial factor after UCS. The moisture content has an impact of 0.68 and pushes the cumulative percentage to 72%, indicating that moisture also plays a considerable role. The WBD shows an impact of 0.60, increasing the cumulative percentage to 87%. Its contribution is significant but lower compared to the previous factors. The RQD has the lowest impact (0.55) but raises the cumulative percentage to 100% indicating that it is the least significant factor among those analyzed. Therefore, the RQD and the friction angle (ϕ) are not considered for the analysis of excavatability. The red line represents the cumulative percentage. As more rock properties are considered, the cumulative impact on excavation performance increases with cohesion, UCS, and tensile strength contributing the most to the total impact.

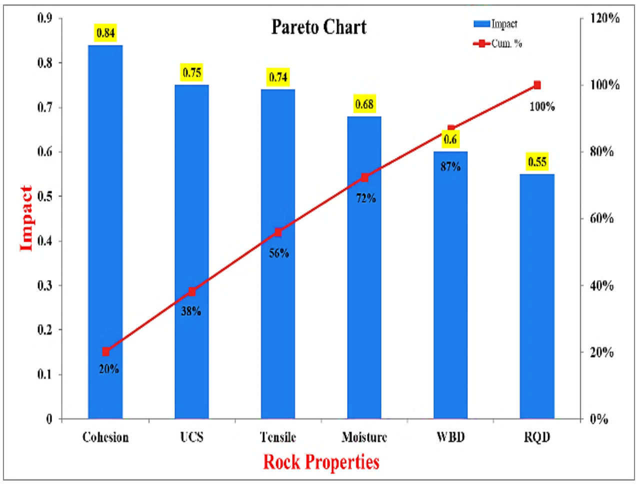

Fig. 7. Pareto Analysis For The Impact Of Rock Properties On Excavation Performance Of Shovel

To predict the excavatability using the rock mass properties, a multiple regression analysis approach is effective, as it allows for the combination of various rock characteristics to develop an empirical model. In this context, the model was created using the excavation performance data from the shovel (TLT) as the dependent variable for 134 trucks allocated to shovels working at various levels of the pit, and the corresponding rock properties as independent variables.

The regression analysis performed using five independent variables revealed that the predictors such as C (kPa), UCS (MPa), and M (%) have statistically significant relationships with the dependent variable. However, TS (MPa) and WBD (t/m^3) do not have significant p-values, meaning that they do not contribute to the model. Therefore, the model was further analyzed, removing the insignificant predictors (TS and WBD) to improve the statistical significance. The correlation coefficient (R) of the improved model indicates a strong positive correlation between the observed and predicted values of the dependent variable (TLT). It shows that the model's predictions are strongly related to the actual outcomes. The coefficient of determination (R^2) shows that about 76% of the variance in Total Loading Time (TLT) is explained by the independent variables (C, UCS, M), indicating that the model is a good fit. Adjusted R square of 0.75 is slightly lower than the R^2 explaining the model is well-fitted but does not overfit the data. A standard error of 27.57 represents the average distance between the observed values and the predicted values (residuals). A lower standard error indicates better predictive accuracy of the model. The higher F-statistic value (35.033) validates the overall statistical significance of the model, and it fits the data well. The p-value associated with the F-statistic is zero, which is less than the typical threshold of 0.05. This confirms that the overall regression model is statistically valid, and at least one of the predictors has a significant influence on the dependent variable.

The developed regression model for the estimation of TLT from rock properties is expressed in eqn. 3:

$$TLT = 29.3\ UCS + 0.4\ C - 0.92\ M + 167.26 \quad (3)$$

Here, TLT = Total truck loading time (sec),

UCS = Uniaxial compressive strength (MPa),

C = Cohesion (kPa),

M = Moisture content (%).

The developed model has a strong correlation between TLT and rock properties, as indicated by the high R-squared value in the analysis. This suggests that the linear combination of these rock properties can explain a substantial portion of the variability in TLT. The results are significant within a 95% confidence interval, implying that the predictions made by the model are statistically reliable. The intercept (167.26) indicates that when all predictors (C, UCS, M) are zero, the TLT is expected to be 167.26 seconds. For every 1-unit increase in UCS (MPa), the TLT increases by approximately 29.3 seconds, and the low p-value (0.00) indicates that this variable is significant and plays a critical role in the model. Similarly, a 1-unit increase in C (kPa) increases the TLT by 0.40 seconds, and a lower p-value (0.00) also makes it a statistically significant parameter. In the case of predictor M (%), an inverse relationship was indicated with a coefficient of 0.92 and p-value of 0.00 validating its implication on the TLT.

Additionally, the variance inflation factor (VIF) analysis was performed to check the multicollinearity (correlation among the independent variables) that exists in the models. VIF values indicate how much a predictor's variance is inflated due to multicollinearity. VIF values less than 1 indicate no multicollinearity, between 1 to 5 indicate moderate multicollinearity (acceptable), and greater than five indicate multicollinearity (not acceptable).

Tables 2-5 present the summary and validation of the regression model and interpretation of corresponding metrics.

Table 2

Regression statistics

Metric	Value
Multiple R	0.87
R-square	0.76
Adjusted R-square	0.75
Standard Error	27.57
Observations	134

Table 3

ANOVA table

Source of Variation	df	SS	MS	F	Sig. F
Regression	3	307,967	102,655.7	135.033	0.0000
Residual	130	98,829.6	760.22877		
Total	133	406,796.6			

Table 4

Coefficients and statistical significance

Variable	Coefficient	Standard Error	t-Stat	p-value	Lower 95%	Upper 95%
Interc	167.26	6.34	26.	0.0	154.	179.
C	0.40	0.06	7.1	0.0	0.29	0.51
UCS	29.29	5.10	5.7	0.0	19.2	39.3
M (%)	-0.92	0.23	-	0.0	-	-047

Table 5

Variance Inflation Factor (VIF) analysis

Variable	R^2	VIF
C (kPa)	0.664	2.97
UCS (MPa)	0.644	2.80
M (%)	0.0005	1.00

5. Excavation Performance Assessment

The K-nearest Neighbors (KNN) algorithm for classification was applied to classify the digging behavior of the shovel, specifically for understanding the digging ease of the rockmass. This was done by dividing the TLT values into four distinct classes. Each class represents distinct levels of performance in terms of how easily the shovel can dig through various rock and soil zones. The TLT values reflect the performance of the shovel in different rock mass conditions based on various rock properties. KNN analysis was performed using the R-Project software. Based on the performance of shovels in different rock and soil zones, the TLT data was classified into three, four, and five classes. The k initial k value (k=12) was determined using the "Square Root of N rule", where N represents the total number of data points analyzed.

Additionally, the model's performance was also evaluated for different values of k by performing grid-search and cross-validation techniques and determining the optimal k value. It was observed that the optimal number of neighbors (k=7) is significantly lower than the initial value of 12. This means that fewer but more relevant neighbors improve the classification performance. Using distance-based weighting helps prioritize closer neighbors, which is useful in regions with varying data densities (i.e., densely, and sparsely populated areas of TLT data).

The Manhattan distance metric (L1 distance) seems to work better for this data set compared to Euclidean distance. This may be because the data distribution follows a more grid-like or stepwise pattern, where straight line (L2) distance does not capture the true difference between the points as effectively. The cross-validation accuracy for the optimized model is 99.43. The KNN model minimizes the variability between classes, ensuring that each class is distinct in terms of excavation difficulty.

Furthermore, for practical improvements, the excavation classes were extended by analyzing the frequency distribution of the existing TLT data. The histogram (Fig. 8) is a graphical representation of the extended excavation classes.

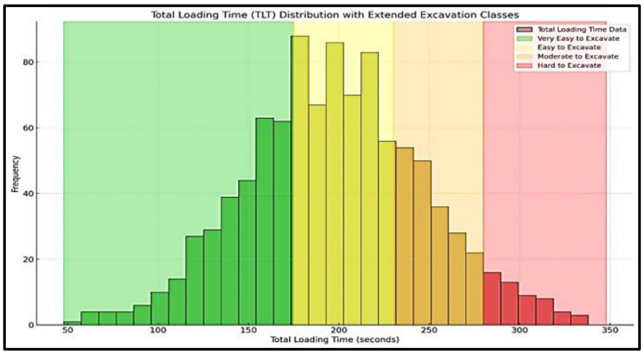

Fig. 8. Graphical Representation Of Excavatability Classes Based On TLT

It can be observed that the green shaded region represents Excavatability Class-I, described as Very Easy to excavate. The histogram shows a high frequency of occurrences, reflecting that most of data points fall within this range. The blue-shaded portion of the histogram indicates Excavatability Class-II, described as Easy to excavate. The frequency distribution peaks here, indicating a large concentration of data within this range. Excavatability Class-III, described as Moderate to excavate, is represented by the orange shaded region of the histogram. There is a noticeable cluster of data points in this range, though the frequency is slightly lower than in the previous class. Highlighted in the red portion of the histogram indicates the Excavatability Class-IV, described as Hard to excavate. Data in this range are sparser but still significant, with a consistent distribution up to around 370 seconds.

The frequency distribution analysis shows that the data are normally distributed across the four classes, but with noticeable peaks in the "Very Easy" and "Easy" categories, suggesting that a huge portion of the materials are easy to manage.

The summary of classification is presented in Table 6.

Table 6

Excavatability classification for soft sedimentary rocks

Excavatability Class	KNN TLT Ranges (sec)	Extended TLT Ranges (sec)	Rockmass description	Interpretation
Class-I (Very Easy)	130 – 171	< 175	Very Low UCS, no cohesion, high moisture	Represent zones with the easiest digging condition, shovel performs efficiently.
Class-II (Easy)	178 – 225	175 – 230	Low UCS, low cohesion, average moisture	Represent zone with the normal digging condition, shovel performs well.
Class-III (Moderate)	232 – 277	231 – 280	Moderate UCS, high cohesion, low moisture	Represent zones with moderate digging difficulty, shovel takes a reasonable amount of time to load material.
Class-IV (Hard)	> 284	> 280	Moderate UCS, average cohesion, exceptionally low moisture	Represent areas with the most difficult digging conditions, shovel takes a much longer time to load a truck.

The application of KNN in Thar is new in context of real-time categorization for softer overburden and coal. The study achieved significant accuracy for classifying excavation difficulty, aligning with global benchmarks, despite the unique geological characteristics of the region. The KNN algorithm is a non-parametric, linear modeling-based classification technique. Therefore, this study does not address the non-linear relationships between rock mass properties and excavatability. Despite these limitations, the findings of this study offer practical benefits such as, optimization of excavation operations, improved equipment selection and matching, cost reduction and resource allocation, adaption to varying rock mass behavior, and short-term planning in open-pit mines.

6. Conclusions

The analysis conducted on shovel operation data through real-time performance assessments, rockmass properties, correlations, and machine learning techniques provides a comprehensive understanding of the factors influencing excavation performance in various rockmass conditions. A significant positive correlation was found between Total Loading Time (TLT) and various rock properties, particularly uniaxial compressive strength (UCS), cohesion (C), and moisture content (M), while an inverse relationship was observed with wet bulk density (WBD). The Pareto analysis further highlighted cohesion, UCS, and tensile strength as the most impactful properties affecting shovel excavation performance, accounting for a cumulative 56% of the total effect. This insight underscores the importance of these properties in understanding rock excavatability and optimizing shovel performance.

The multiple regression model developed using TLT as the dependent variable and significant rock properties (C, UCS, M) as predictors demonstrated a strong correlation (R=0.76) and explained 76% of the variance in TLT. This model, validated with high R-squared and F-statistic values, shows that the selected rock properties are robust predictors for estimating excavation performance. Removing statistically insignificant predictors, such as tensile strength and wet bulk density, improved the model's accuracy and predictive reliability, achieving a 95% confidence interval for the predictions. Variance inflation factor (VIF) analysis confirms that the model's predictors do not exhibit problematic multicollinearity, thus supporting the model's stability.

The application of K-nearest neighbors (KNN) for classifying TLT data into four classes based on rockmass properties provides additional insights into the ease of excavation. By optimizing the k-value and employing Manhattan distance as the metric, the model achieved an impressive 99.43% accuracy, affirming the effectiveness of KNN in distinguishing between different excavatability classes. The frequency distribution of TLT data and the histogram visualization of extended excavation classes underscore the distribution patterns within the classes. The frequency distribution illustrates a predominance of "Very Easy" and "Easy" classes, indicating that majority of the materials within the pit are simple to excavate, while smaller portions fall under more challenging classes.

In conclusion, this study emphasizes the critical role of rock properties, particularly cohesion, UCS, and moisture content, in determining shovel excavation efficiency. The combination of regression and KNN classification analyses provides a robust framework for predicting and categorizing excavation performance. These findings can be leveraged to optimize excavation strategies, improve operational efficiency, and support real-time decision-making in surface mining operations. Specifically, the shovel deployment based on such criteria will effectively reduce time losses involved in material handling process and increase overall equipment effectiveness (OEE). Future work may expand on these findings by integrating additional machine-learning techniques and exploring non-linear models such as Decision Trees, Random Forests, Support Vector Machines (SVM) to capture more complex relationships between rock properties and excavation performance.

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