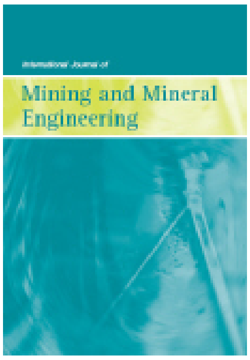

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Segregation of rock properties using machine learning algorithm with Euclidean distance

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Abstract: In rock drilling applications, abrasion causes wear in inserts and hostile working conditions cause damage to other bit components. The effects of physico-mechanical properties of rock on the tool wear are investigated by several researchers in the past. So, it becomes imperative to exhibit good scalability of rock properties by segregating rock samples having similar properties for natural homogeneous rock property groupings. The aim of this work is to segregate groups with similar type of rock properties and assign them into a cluster. This work considers a machine learning based hierarchical clustering approach to segregate groups of rock with similar traits. The results obtained from this study initiate a conversation on the proper choice of rock and tool material for doing laboratory studies using wear test apparatus. The analysis's findings map the distinct qualities of the rock for different mining areas by classifying groups of rocks with comparable characteristics.

Keywords: rock properties; clustering; machine learning; Euclidean distance; rock mechanics; drilling; rock sample; artificial intelligence; tungsten carbide; clustering algorithm.

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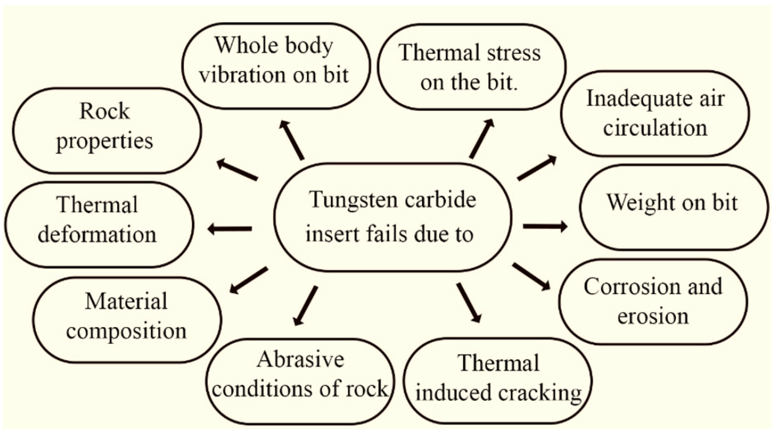
Biographical notes: Satya Prakash obtained his Doctoral degree from the Department of Mechanical and Mining Machinery Engineering at the Indian Institute of Technology (Indian School of Mines), Dhanbad. He is actively engaged in research, with his primary areas of interest being machine learning, tribology, rock mechanics, reliability studies, coatings, and tool design.

1 Introduction

During drilling, the cases of premature failures of drill bits found to be a common phenomenon in terms of insert failures. Moradizadeh et al. (2016) investigations showed that the drill bit lifetime per meter of drill hole drilled by a bit (m/bit) decreases with an increase in equivalent quartz content. The wear of inserts due to rock abrasivity in bits reduces the level of performance of the drilling operation (Yaralı et al., 2008). The current reasons for tool failure are a rise in temperature, noise, and vibration. Sato et al.

(2013) reported that rising temperatures during drilling accelerate insert wear. The combined effect of rock properties and temperature rise in polycrystalline diamond compact (PDC) drill bits was explored by Appl et al. (1993). Shankar et al. (2020) reported that the bit-rock interface temperature plays a major role in the wear rate of the tungsten carbide (WC) drill bit during drilling conditions. Piri et al. (2021) have reported that the noise level and whole-body vibration strongly influence wear in inserts. Figure 1 depicts the integrated challenges for tungsten carbide inserts (TCI) under abrasive conditions.

Figure 1 Reasons of TCI failure under different conditions (see online version for colours)



Scientific investigations have always been carried out to develop new drill bit insert materials and their components. The lack of real-life data on wear parameters from mines often remains indecisive. Developing new insert materials requires a series of laboratory experiments with various parameters, including rock properties. Still, most of the researchers have not considered state-of-the-art machine learning techniques in their studies to improve tool wear conditions in rock drilling applications.

Machine learning is the branch of artificial intelligence and has the potential to solve complex problems related to rock mechanics by providing significant solutions. Mozaffar et al. (2019) have taken advantage of machine learning algorithms to identify the unknown relations and mapped input and output parameters for their laboratory results obtained from experiments. Researchers have utilised data-driven learning methods to predict effective correlations for complex problems in rock mechanics (Gu et al., 2018; Liang et al., 2018). The different models such as support-vector machines, linear regression model, clustering, deep learning, adoptive boosting algorithm, and kernel and nearest-neighbour non-parametric regression models have been identified by researchers in various fields of engineering problems to determine the positive outcome for complex problems (Yao et al., 2014; Ghosal et al., 2020; Li et al., 2022; Altman, 1992). The information (Azarafza et al., 2019, 2022; Cemiloglu et al., 2023; He et al., 2019, 2021, 2023; Wang et al., 2022, 2023; Kumar and Chandar, 2023; Steiakakis et al., 2019) given in Table 1 represents machine learning and artificial intelligence utilisation in mining engineering.

Table 1 Recent developments in mining using machine learning

Sl. no.	*Authors*	*Title*	*Findings of the study*
1	Mohammad Azarafza, Akbar Ghazifard, Haluk Akgün and Ebrahim Asghari-Kaljahi (2019)	Geotechnical characteristics and empirical geo-engineering relations of the South Pars Zone marls, Iran	Using regression analysis, an empirical relationship has been obtained between the physico-mechanical properties and geo-engineering features of the soft rock (marls). The results were reliable.
2	Mohammad Azarafza, Masoud Hajialilue Bonab and Reza Derakhshani (2022)	A deep learning method for the prediction of the index mechanical properties and strength parameters of Marlstone	The proposed deep learning-based predictive model (DNN) estimates the geomechanical characteristics of marlstone samples. This study verified the model using benchmark learning classifiers and concluded that the proposed DNN-based model led to the highest accuracy and depicted the lowest error rate.
3	Ahmed Cemiloglu, Licai Zhu, Sibel Arslan, Jinxia Xu, Xiaofeng Yuan, Mohammad Azarafza and Reza Derakhshani (2023)	Support vector machine (SVM) application for uniaxial compression strength (UCS) prediction: a case study for Maragheh Limestone	This study uses an SVM-supervised machine learning approach to predict limestone rock's compressive strength (UCS). Further, this work meticulously validated the model using a confusion matrix, loss functions, and error tables.
4	Mingming He, Zhiqiang Zhang, Jie Ren, Jiuyang Huan, Guofeng Li, Yunsheng Chen and Ning Li (2019)	Deep convolutional neural network for fast determination of the rock strength parameters using drilling data	The authors present a novel strategy to determine the field strength parameters of rock by consolidating a profound convolutional neural network (DCNN) procedure using drilling data. The approach shows potential for field applications in rock engineering.
5	Mingming He, Zhiqiang Zhang, Jiwei Zhu, Ning Li, Jie Ren, Guofeng Li and Yunsheng Chen (2021)	Correlation between the rockburst proneness and friction characteristics of rock materials and a new method for rockburst proneness prediction: field demonstration	This study presented a novel strategy to predict the rockburst proneness of rock materials using drilling data. The results from this work were highly reliable.
6	Haoteng Wang, Mingming He, Zhiqiang Zhang and Jiwei Zhu (2022)	Determination of the constant m(i) in the Hoek Brown criterion of rock based on drilling parameters	Authors developed the new models to predict the triaxial compressive strength (TCS), internal friction angle φ, and cohesion c of rock. The results of this study can be applied to rock engineering.
7	Mingming He, Jiapei Zhou, Panfeng Li, Beibei Yang, Haoteng Wang and Jing Wang (2023)	Novel approach to predict the spatial distributions of hydraulic conductivity of rock mass using convolutional neural networks	This research proposes the design of convolutional neural networks (CNNs) to anticipate the spatial distributions of hydraulic conductivity based on restricted geological parameters.
8	Haoteng Wang, Mingming He, Jianbin Zhao and Yonghao Zhang (2023)	Digital drilling-based determination of rock anisotropy and anisotropic effect on cutter wear	This work proposed a digital drilling strategy to assess the mechanical anisotropy of rock and the anisotropic impact on cutter wear.
9	Mittapally Sathish Kumar and Karra Ram Chandar (2023)	Development of an alert system in slope monitoring using wireless sensor networks and cloud computing technique – a laboratory experimentation	In their study, the authors presented microelectromechanical sensors, the internet of things (IoT), and cloud computing techniques for slope monitoring to prevent potential failures in harsh mining conditions.
10	Chrysanthos Steiakakis, Georgia Papavgeri, Nikos Steiakakis, Zach Agioutantis and Paul Schilizzi (2019)	A cloud-based near real-time slope movement monitoring system	The authors discussed a reliable cloud-based system that delivers alarms in slope monitoring applications in mining.

Rock is an anisotropic and non-homogeneous material described by its structure, chemical composition, and texture. It is essential to understand the rock material properties to measure the reliability of drill bits and wear of drill bit inserts (Abbas, 2018). In this paper, rock samples were obtained from the drilling locations, and the physico-mechanical properties of the rocks were measured from representative rock samples prepared in the laboratory complying with International Society of Rock Mechanics (ISRM) standards (Hatheway, 2009). The physico-mechanical properties of sandstone rock, such as dry density, porosity, P-wave velocity (Vp), uniaxial compressive strength (UCS) and modulus of elasticity (E), Cerchar abrasivity index (CAI), and Cerchar hardness index (CHI) have been considered in the present study. A hierarchical agglomerative machine learning-based clustering approach has been derived from the obtained rock properties to understand the impact of different rock properties on mining locations. The present hierarchical agglomerative clustering approach not only segregates the different mining locations based on rock properties but will also help in the process of data collection of appropriate rock samples for wear tests in various studies based on needs. Further, this study reduces the sample's invariability in laboratory tests for similar types of rock data and also reduces the overall cost of experiments. This work also provides a better understanding of designing experiments and selecting tools in drilling applications.

2 Methodology

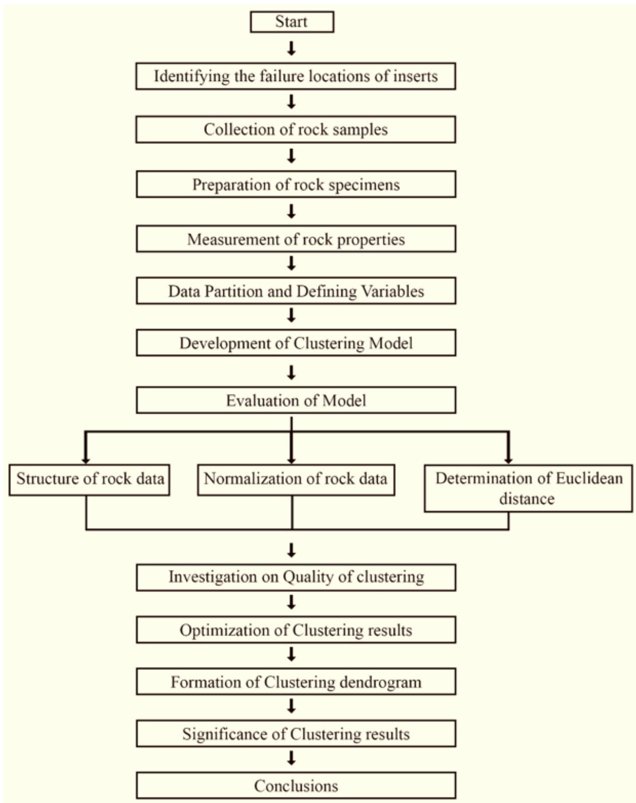
The research methodology provides the steps to be followed and presents a clear map for the problem statement. Figure 2 depicts the flowchart that was considered in this study.

2.1 Preparation of rock test specimens

The author utilises the Nevada Chart Data Analysis technique to understand the failure condition of drill bits based on drilling locations. The details on Nevada chart data analysis can be found elsewhere (Prakash and Mukhopadhyay, 2020). The significant advantage of this technique is that it works on warranty-based data without large-scale assumptions and data manipulations. Based on the failure conditions of drill bits in the Nevada Chart, rock block samples were collected from the field as per the ISRM standards (Hatheway, 2009). Sandstone rock (block size: 300 mm × 300 mm × 200 mm) samples were gathered from 30 different drilling locations of the mine. Cylindrical core samples of size 54 mm dia. ×180 mm height were prepared from the sandstone rock samples using a core drill machine. The prepared samples were ground using a grinder and polished with a corundum abrasive powder.

Two samples for UCS and three samples for BTS have been prepared from each sandstone block. In the sample preparation process of UCS, the length-to-diameter ratio was kept greater than 2.5. Initially, the prepared samples for the UCS test were taken for the Cerchar hardness test (CHI). After performing the CHI test, the drilled section developed by a miniature drill machine was removed, and the samples were polished as per the ISRM standards (Hatheway, 2009). Further, the polished UCS samples were taken into the study for the density, P-wave velocity, and porosity test. The density, P-wave velocity, and porosity tests are the non-destructive test. The unpolished BTS samples were used for the Cerchar abrasivity test. In the study, four numbers of samples have been considered for density, porosity, CHI, P-wave velocity, and UCS test. Two samples (from each sandstone block) were used for the CAI test. Six samples (three from each sandstone block) were used for the BTS test. All test samples were prepared as per ISRM standard (Hatheway, 2009). A few prepared rock samples for laboratory tests are shown in Figure 3.

Figure 2 Flowchart representing the various steps in the methodology (see online version for colours)



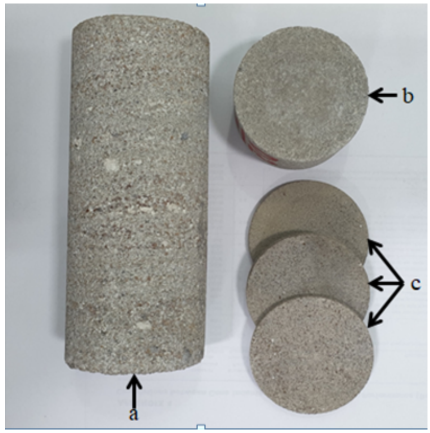
2.2 *Measured values of rock properties*

The measured values of physico-mechanical properties of sandstone rock samples collected from 30 different mine locations are presented in Table 2. The measured data in Table 2 discloses that high density and low porosity rock usually possessed higher UCS values. The sonic velocity Vp was found greater than 3 for the tested samples, indicating that the grains inside the rock sample are closely packed. The behaviour of sonic velocity with different rocks can be found elsewhere (Ramamurthy, 2004). Further, the authors have discussed and estimated each rock property's significance for the dependent variable UCS using a Pareto chart (Prakash and Mukhopadhyay, 2020) to interpret the relationship between the rock properties. For the Pareto chart analysis, the dependent variable was UCS, whereas the independent variables were dry density, porosity, CHI, BTS, Vp, and E.

Table 2 The measured rock properties

Mining locations	*Dry-density (KN/m^3)*	*Porosity (%)*	*Cerhar hardness index*	*Brazilian tensile strength (MPa)*	*Sonic-velocity (P-wave velocity) (m/s)*	*Youngs-Modulus (GPa)*	*Cerchar abrasivity index*	*Uniaxial compressive strength (MPa)*
Mine-Area1	21.63	4.71	21.9	7.25	4.1	6.67	2.55	39.96
Mine-Area2	21.54	3.41	22.8	5.21	3.69	6.41	2.9	35.17
Mine-Area3	21.66	1.63	26.4	5.19	4.4	9.47	3.05	50.01
Mine-Area4	21.78	4.4	17.3	5.71	3.86	5.23	2.75	31.96
Mine-Area5	21.44	3.36	18.9	5.62	3.44	5.51	2.75	35.21
Mine-Area6	22.55	2.39	37.6	9.86	4.61	9.92	3.1	63.16
Mine-Area7	22.67	2.11	33.1	10.49	4.21	9.78	2.57	63.49
Mine-Area8	21.32	5.32	17.4	5.37	3.61	4.41	2.51	29.34
Mine-Area9	22.2	3.27	26.4	8.86	4.07	8.98	2.67	48.97
Mine-Area10	23.69	1.24	28.7	11.24	5.1	11.34	3.2	81.9
Mine-Area11	22.36	1.43	36.6	9.79	4.9	11.21	2.97	78.98
Mine-Area12	22.18	2.81	25.7	8.46	3.92	6.71	3.42	53.01
Mine-Area13	21.68	3.14	28.3	6.98	4.87	8.68	2.45	58.06
Mine-Area14	22.29	1.89	27.6	7.49	4.21	10.5	2.65	61.09
Mine-Area15	22.7	3.91	26.7	7.36	4.59	7.78	2.55	56.14
Mine-Area16	22.61	2.44	37.4	10.65	4.72	10.76	3.13	63.1
Mine-Area17	23.24	1.28	31.98	9.83	4.87	10.98	2.93	81.7
Mine-Area18	23.39	1.33	35.1	11.01	4.76	10.81	3.51	79.37
Mine-Area19	22.42	2.4	34.6	10.78	4.57	10.71	2.55	62.96
Mine-Area20	21.46	5.31	19.8	4.98	3.32	4.56	2.65	32.13
Mine-Area21	23.21	1.29	31.7	9.98	4.31	10.98	2.5	78.76
Mine-Area22	23.19	1.34	33.9	10.91	4.88	11.23	3.44	81.1
Mine-Area23	22.36	3.36	25.2	6.4	4.18	9.49	3.41	50.42
Mine-Area24	23.54	2.78	27.7	10.6	4.08	5.89	2.9	67.98
Mine-Area25	22.79	1.89	33.6	10.51	4.21	10.88	2.72	64.93
Mine-Area26	22.2	3.13	25.8	7.78	4.21	7.98	3.3	52.76
Mine-Area27	23.96	1.18	26.7	11.76	5.62	11.44	2.96	82.65
Mine-Area28	21.96	1.57	34.6	8.77	5.34	11.78	2.46	75.76
Mine-Area29	21.07	1.78	27.7	9.74	4.22	7.76	2.52	47.97
Mine-Area30	22.31	2.71	31.8	9.32	3.98	9.31	3	62.54

Figure 3 Prepared rock test samples for physico-mechanical test



A statistical analysis representing the mean, standard deviation, median, median deviation, skewness, kurtosis, and standard error pertaining to the estimated rock properties is shown in Table 3.

Table 3 Represents the statistical results on the tested samples for each rock's properties

Sl. no.	*Mean*	*Standard deviation*	*Median*	*Median absolute deviation*	*Skewness*	*Kurtosis*	*Standard error*
Dry-density	22.38	0.76	22.34	0.90	0.28	–0.89	0.14
Porosity	2.63	1.22	2.42	1.33	0.68	–0.53	0.22
CHI	28.43	5.85	27.70	6.81	–0.24	–0.93	1.07
BTS	8.60	2.14	9.09	2.44	–0.35	–1.36	0.39
P-wave velocity	4.36	0.54	4.22	0.54	0.22	–0.45	0.10
Youngs Modulus	8.91	2.29	9.48	2.37	–0.55	–1.12	0.42
CAI	2.87	0.33	2.83	0.41	0.46	–1.11	0.06
UCS	59.02	16.68	61.81	19.79	–0.19	–1.14	3.04

From Table 2, it can be observed that the rock specimens comprise a varied range of rock properties. Kurtosis measures the distribution's tailedness and estimates the dataset's outlier data. The considered data in Table 2 is acceptable for statistical analysis as the kurtosis estimation for each rock properties lie in between –2 to +2. The details on Kurtosis can be found elsewhere (Cain et al., 2017).

2.3 *Clustering of rock properties*

Clustering is an advanced and important technique to understand different phenomena. It segregates explicit data from different point of views concluding it into a value added information and provides statistical solutions to data in several fields (Davis and Meyer, 2009; Saxena et al., 2017). For the data shown in Table 2, a clustering investigation has been performed to extract some essential information from the data by observing what groups the data focus falls into when applying a clustering algorithm. In this way, it is the way to gather the data points of rock property into clusters so that one could be able to investigate the significance of rock properties based on different mining locations. Thus, the objective of clustering analysis is to understand the impact of rock properties on the mining locations. The clustering analysis in this study discusses the following issues:

1 How to classify the mining area based on the rock properties?

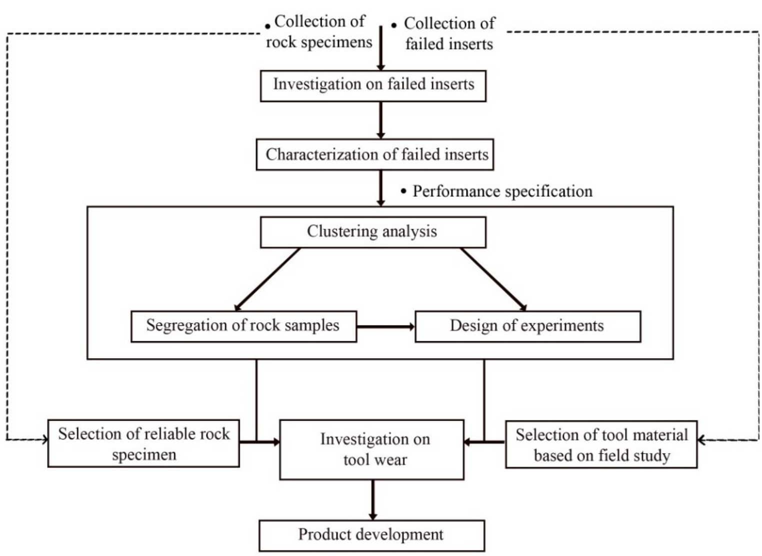
2 How to quantify the significance of individual rock properties with respect to the mining locations?

3 Based on the mining locations, whether these rock properties have a similar or dissimilar impact on bit failure?

The clustering analysis performed in this study has been developed using R codes in software R (Core Team, 2013). R is a language and environment for statistical computing and graphics.

A study on failed bits obtained from the field is crucial as it provides significant information on failed inserts regarding life estimation. In the field, drill bit fails for many reasons, and one of the reasons is the rock characteristics of that location. Researchers have thoroughly studied the failure mode of insert obtained from the field and simultaneously developed test setups for their betterment. However, the correct assessment of the inserts is challenging due to rock characteristics. In Figure 4, a methodology to address this problem is provided. The developed clustering process in this study is a method to guide interface design between the failed and newly developed bits.

Figure 4 Practical tool selection strategies in consideration of clustering analysis

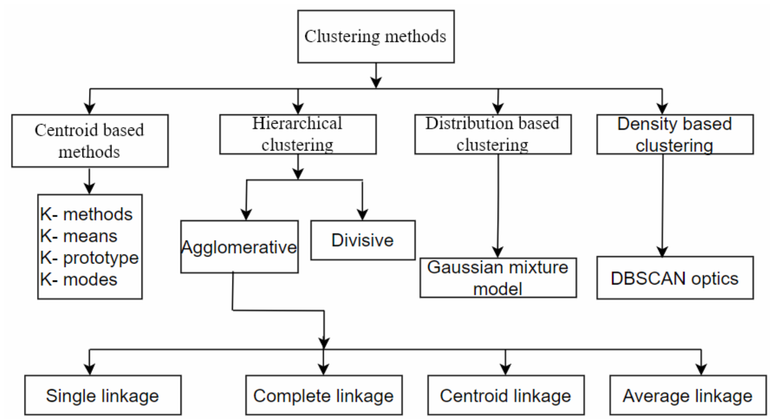


The new bits are created in the laboratory by a series of investigations. In the case of TCI, researchers tested the pin sample of TCI against the rock surface for the determination of tool characteristics. However, to estimate the accurate solution on tool wear, utilising the rock specimen from the exact field location is essential. Clustering here investigates the rock sample characteristics and segregates them into groups according to their properties. By segregating rock samples for the wear test setup using clustering, a reliable solution may be achieved in the case of insert material. These insights gained through the clustering approach help with the selection of tool material for a drilling application.

3 Clustering methodology

Clustering methodology can be categorised into four effective methods. They are appeared in Figure 5. Each method has its advantages and hence can be used on the basis of data characteristics (Rokach and Maimon, 2010).

Figure 5 Different types of clustering methods



Source: Rokach and Maimon (2010)

The present work discusses a hierarchical-based agglomerative clustering approach to rock data since this approach is the prominent and widely used technique to analyse data with multiple variables. The steps involved in this approach are discussed below.

3.1 Structure of rock data

The first step is to understand the data type. For the clustering analysis, the data are drawn from Table 2. The data frame consists of 30 observations with nine variables in which the eight variables, such as dry density, porosity, CHI, BTS, sonic velocity, Youngs modulus, CAI, and UCS, are of numeric type. The mining area is the 9th variable of factor type with 30 different levels, such as mine area 1, mine area 2 ,….., mine area 30.

3.2 Normalisation of rock data

The clustering calculation must not be one-sided with regards to the variables having higher values only. Table 2 shows that UCS values are more with respect to other variables. Also, all these numeric variables are not present on the same scale. This may prompt inappropriate clustering results, and because of this, the clustering results' effectiveness will decrease.

To conquer this issue, clustering algorithm will bring down all the numeric variables shown in Table 2 together to a similar scale. One of the most widely recognised methods to do so is normalisation, where this approach ascertains the mean and standard deviation of the variable and with these boundaries, the objective of normalisation is to change the estimations of the numeric column in the dataset to a typical scale, without twisting contrasts in the scopes of qualities.

In other words, the normalisation procedure gives equal importance to all the variables irrespective of their magnitude value. The standardised scale function in 'software R (Core Team, 2013)' has been used to compute the normalised values for the variables discussed in Table 2. For each numeric variable shown in Table 2, mean and standard deviation values have been computed. The scale function is a generalised method to determine a normalised value for any dataset. This is also called a data transformation technique, which is used for regression and clustering analysis. The normalised value using the scale function is simply the number of standard deviations away from the mean. In the study, the normalised value has been computed by using the following formula:

$$z_i = \frac{x_i - \overline{x}}{s}$$

where

z_i normalised value of rock properties

x_i given value of rock property

$\overline{x}$ mean value of the corresponding rock property

s standard deviation of the corresponding rock property.

In this step, all the variables' normalised values are calculated using clustering algorithms, which are shown in Table 4. Here, the normalisation technique gives equal importance to all the variables before estimating each property's significance. Table 4 depicts that all variables are on the same scale as the magnitude is reduced for all the variables.

3.3 Calculating the Euclidean distance

Euclidean distance that depicts the distance between two points based on the Pythagoras theorem is one of the most utilised algorithms in the cluster investigation (Zendrato et al., 2020). The Euclidean distance for the normalised dataset shown in Table 4, has been calculated to find the similarities between the mining locations for the different rock properties. The calculated Euclidean distance in consideration with the rock properties by considering clustering algorithm is shown in Table 5. In Table 5, the integer numbers 1, 2, 3, …, 30 are the different mining locations and represent mine area 1, mine area 2,…., and mine area 30, respectively. The Euclidean distance between these mining locations is represented in a matrix form (refer to Table 5).

Table 4 Normalised values for rock properties

Mine-area	*Dry-density*	*Porosity*	*CHI*	*BTS*	*Sonic velocity (P-wave)*	*Youngs modulus*	*CAI*	*UCS*
1	–0.9912	1.7110	–1.1174	–0.6282	–0.4824	–0.9761	–0.9703	–1.1428
2	–1.1101	0.6432	–0.9635	–1.5799	–1.2384	–1.0896	0.0942	–1.4300
3	–0.9515	–0.8189	–0.3477	–1.5892	0.0706	0.2465	0.5505	–0.5402
4	–0.7929	1.4564	–1.9043	–1.3466	–0.9249	–1.6049	–0.3619	–1.6225
5	–1.2423	0.6021	–1.6306	–1.3886	–1.6993	–1.4826	–0.3619	–1.4276
6	0.2246	–0.1946	1.5681	0.5893	0.4578	0.4430	0.7026	0.2482
7	0.3832	–0.4246	0.7983	0.8832	–0.2796	0.3819	–0.9094	0.2680
8	–1.4009	2.2121	–1.8872	–1.5052	–1.3859	–1.9630	–1.0919	–1.7796
9	–0.2378	0.5281	–0.3477	0.1228	–0.5377	0.0326	–0.6052	–0.6025
10	1.7313	–1.1393	0.0457	1.2331	1.3613	1.0631	1.0068	1.3720
11	–0.0264	–0.9832	1.3970	0.5567	0.9925	1.0064	0.3072	1.1969
12	–0.2643	0.1503	–0.4674	–0.0637	–0.8143	–0.9586	1.6759	–0.3603
13	–0.9251	0.4214	–0.0226	–0.7542	0.9376	–0.0983	–1.2744	–0.0575
14	–0.1189	–0.6054	–0.1424	–0.5162	–0.2796	0.6963	–0.6661	0.1241
15	0.4229	1.0539	–0.2963	–0.5769	0.4210	–0.4914	–0.9703	–0.1726
16	0.3039	–0.1536	1.5339	0.9579	0.6606	0.8099	0.7938	0.2446
17	1.1366	–1.1065	0.6068	0.5753	0.9372	0.9059	0.1855	1.3600
18	1.3348	–1.0654	1.1405	1.1258	0.7344	0.8317	1.9497	1.2202
19	0.0528	–0.1864	1.0549	1.0185	0.3841	0.7880	–0.9703	0.2362
20	–1.2159	2.2039	–1.4766	–1.6872	–1.9206	–1.8975	–0.6661	–1.6123
21	1.0969	–1.0982	0.5589	0.6453	–0.0952	0.9059	–1.1223	1.1837
22	1.0705	–1.0572	0.9352	1.0792	0.9557	1.0151	1.7368	1.3240
23	–0.0264	0.6021	–0.5529	–1.0247	–0.3349	0.2553	1.6455	–0.5156
24	1.5331	0.1256	–0.1253	0.9345	–0.5193	–1.3167	0.0942	0.5373
25	0.5418	–0.6054	0.8839	0.8926	–0.2796	0.8623	–0.4532	0.3544
26	–0.2378	0.4131	–0.4503	–0.3809	–0.2796	–0.4040	1.3109	–0.3753
27	2.0882	–1.1886	–0.2963	1.4757	2.3201	1.1068	0.2767	1.4169
28	–0.5550	–0.8682	1.0549	0.0808	1.8038	1.2553	–1.2440	1.0038
29	–1.7313	–0.6957	–0.1253	0.5333	–0.2612	–0.5001	–1.0615	–0.6625
30	–0.0925	0.0681	0.5760	0.3374	–0.7037	0.1767	0.3984	0.2111

Table 5 Euclidean distance

Mine-area	*Mine-area*																												
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*
2	1.97																												
3	3.52	2.65																											
4	1.56	1.52	3.76																										
5	2.08	1.04	3.40	1.29																									
6	4.63	4.69	3.32	5.51	5.41																								
7	4.04	4.42	3.51	5.04	4.84	1.98																							
8	2.00	2.39	4.80	1.37	1.92	6.43	5.83																						
9	2.14	2.64	2.65	3.11	3.05	2.87	2.06	3.94																					
10	6.18	6.35	4.65	6.84	6.86	2.91	3.33	7.96	4.38																				
11	5.40	5.50	3.61	6.32	6.14	1.54	2.30	7.24	3.59	2.46																			
12	3.38	2.71	2.70	3.45	3.26	3.14	3.52	4.54	2.55	4.46	4.08																		
13	2.63	3.34	2.60	3.74	3.83	3.25	2.78	4.40	2.07	4.71	3.44	3.71																	
14	3.41	3.38	2.04	4.17	3.87	2.63	1.82	5.07	1.67	3.74	2.74	3.11	2.07																
15	2.26	3.13	3.09	3.22	3.58	3.21	2.64	4.01	1.65	4.42	3.82	3.22	1.69	2.27															
16	4.92	5.08	3.66	5.84	5.78	0.57	2.14	6.77	3.12	2.68	1.51	3.45	3.53	2.90	3.50														
17	5.48	5.63	3.87	6.27	6.18	2.13	2.30	7.29	3.62	1.41	1.43	4.10	3.73	2.71	3.64	2.08													
18	6.34	6.22	4.55	6.96	6.86	2.28	3.44	8.05	4.51	1.65	2.25	4.03	5.01	3.97	4.75	2.09	1.95												
19	4.23	4.79	3.67	5.39	5.29	1.84	0.93	6.14	2.37	3.32	1.99	3.94	2.63	2.13	2.80	1.87	2.31	3.47											
20	2.18	2.11	4.66	1.49	1.74	6.23	5.72	0.86	3.87	7.87	7.12	4.24	4.52	4.97	4.03	6.60	7.18	7.83	6.09										
21	5.08	5.36	4.04	5.96	5.74	2.71	1.51	6.82	3.15	2.78	2.29	4.38	3.51	2.23	3.38	2.78	1.68	3.28	1.86	6.71									
22	6.20	6.15	4.38	6.87	6.79	2.21	3.31	7.96	4.38	1.40	1.94	4.05	4.76	3.76	4.61	1.99	1.67	0.50	3.27	7.78	3.11								
23	3.38	2.74	2.14	3.51	3.54	3.15	3.72	4.65	2.56	4.37	3.98	1.71	3.42	2.80	2.96	3.40	3.98	4.09	3.95	4.36	4.38	4.03							
24	4.05	4.33	4.20	4.55	4.59	3.05	2.55	5.47	2.76	3.53	3.78	2.80	3.85	3.20	2.76	3.29	3.18	3.63	3.19	5.30	3.04	3.70	3.56						
25	4.47	4.69	3.50	5.41	5.18	1.70	0.72	6.27	2.39	2.90	1.94	3.55	3.16	1.90	3.03	1.77	1.92	2.92	1.09	6.12	1.37	2.79	3.61	2.77					
26	2.99	2.55	2.16	3.26	3.25	2.76	3.19	4.40	2.06	4.14	3.66	0.95	3.03	2.56	2.58	3.06	3.70	3.87	3.48	4.16	4.03	3.81	1.04	2.87	3.21				
27	6.58	7.00	5.34	7.31	7.46	3.77	3.88	8.39	4.94	1.33	3.17	5.38	4.97	4.32	4.72	3.52	2.12	2.86	3.74	8.42	3.21	2.60	5.23	4.14	3.60	4.98			
28	5.19	5.65	3.81	6.29	6.20	2.90	2.75	7.05	3.74	3.62	1.95	5.06	2.71	2.79	3.65	2.91	2.53	4.03	2.15	7.10	2.67	3.67	4.74	4.64	2.74	4.44	3.69		
29	3.03	3.25	2.91	3.91	3.46	3.51	2.68	4.53	2.13	5.12	3.81	3.38	2.36	2.43	3.11	3.77	4.24	5.18	2.82	4.60	3.75	5.00	3.89	3.87	3.10	3.18	5.58	3.63	
30	3.52	3.48	2.70	4.31	4.06	1.65	1.66	5.20	1.69	3.55	2.53	2.13	2.83	1.81	2.56	1.98	2.75	3.19	2.05	4.94	2.65	3.13	2.38	2.44	1.63	1.84	4.46	3.49	2.71

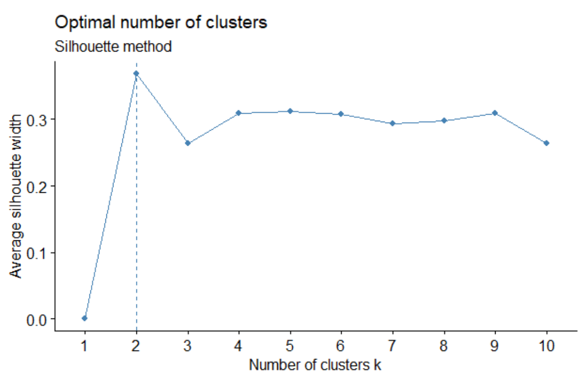
The minimum Euclidean distance for any two mining locations suggests that the two mining areas have similar rock properties and must be grouped together. Table 5 shows that the minimum distance of mine area 1 with respect to any other mining locations is 1.56, and basically, it is the Euclidean distance between mine area 1 and 4. However, the maximum distance of mine area 1 with respect to any other mining areas is 6.58, and it is the distance between mine area 1 and mine area 27. These observations state that mine area 1 and mine area 4 can be grouped together in one cluster since they pose similar rock properties compared to other locations. However, the mine area1 and mine area 27 must not be grouped together since their Euclidean distance is very large. Similarly, the distance between any two mining locations can be obtained and grouped together.

4 Results and discussion

4.1 Determining the optimum number of clusters

Finding the optimum number of clusters for a dataset is the biggest challenge. However, there are many methods available that are helpful for this type of problem. The elbow, silhouette and gap statistics (Nagpal et al., 2013) methods mostly suggest the best optimal number of clusters for any dataset. One can use any of the three methods for their dataset for optimising the results. In this study, the silhouette method has been considered for finding the optimal number of clusters of a dataset shown in Table 4. The graphical representation of the results using the silhouette method is presented in Figure 6.

Figure 6 Optimal number of clusters using the silhouette method (see online version for colours)



Here, the silhouette method suggests the optimum number of clusters for the normalised dataset as 2. This implies that the 30 different mining locations must be divided into two distinct clusters based on rock properties.

4.2 Quality of clustering results

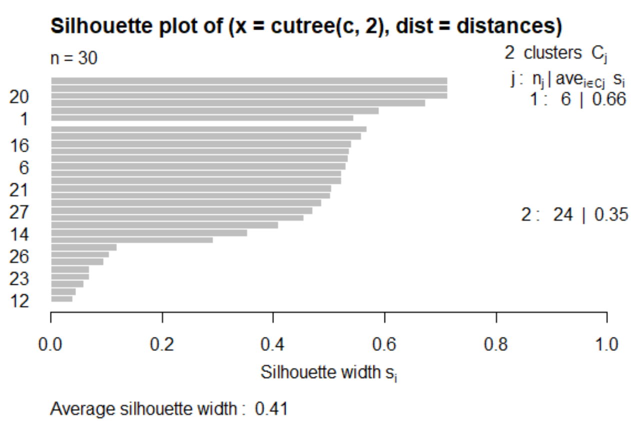
The clustering quality matters in data investigation. The adopted hierarchical-based clustering method estimates clustering quality by evaluating the clustering dendrogram with five different agglomerative linkages. The different agglomerative linkages (Tokuda et al., 2022) are average, complete, single, centroid and median. The quality of clustering mainly depends upon the average silhouette width (Nagpal et al., 2013; Tokuda et al., 2022). The silhouette width is the average distance between clusters. Its value lies between –1 and 1, where 1 represents a good cluster (Golalipour et al., 2021). Since the silhouette method estimates the optimal number of clusters as 2, the authors determined the average silhouette width value for all the five agglomerative linkages to investigate the clustering effectiveness. Table 6 differentiates the quality of clustering based on the average silhouette width value.

Table 6 Clustering results

Agglomerative linkage	*Optimum no of clusters based on the silhouette method*	*Grouping of 30 different mining locations in two clusters*	*Average silhouette width*
Average	2	6.24	0.41
Complete	2	6.24	0.41
Single	2	23.1	–0.03
Centroid	2	6.24	0.41
Median	2	17.13	0.35

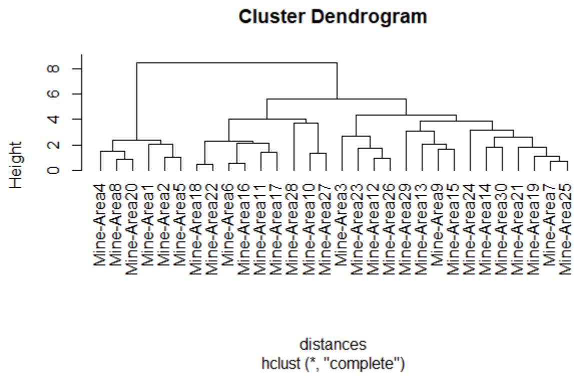
The average silhouette width for the average, complete, and centroid linkages is 0.41, which is maximum compared to the other linkages. This implies that the clustering dendrogram produced by any of these linkages gives the best possible combination to mining locations. From Table 6, these agglomerative linkages also divide the 30 different mining locations into two clusters, with six mining locations in one cluster and the rest mining locations in the second cluster. The following silhouette plot also depicts the same results using complete linkage.

Figure 7 Silhouette plot using complete agglomerative linkage



In Figure 7, n = 30, represents the total number of mining locations, and they have been divided into 2 clusters based on the obtained rock properties. Also, it depicts that the six mining locations of cluster 1 have a similar type of rock formations. However, the other 24 mining locations of cluster 2 have different kinds of rock formations compared to the mining locations of cluster 1. A hierarchical architecture or cluster dendrogram for all the mining location based on the calculated distance matrix is shown in Figure 8.

Figure 8 Cluster dendrogram for the mining locations using complete linkage



The clustering dendrogram shown in Figure 8 implies that the mining areas such as 4, 8, 20, 1, 2, and 5 are grouped in one cluster since the rock properties belong to these areas are more or less similar to each other. However, the mining areas other than these locations have been grouped in the second cluster. The results from cluster means and within the cluster sum of squares were favourable when the data were analysed with the silhouette method. The conditions on an optimal number of clusters and their associated results by considering various agglomerative linkages such as average, complete, single, centroid, and median can be observed in Figure 6, Table 6, and Figure 7 respectively.

4.3 Significance of rock properties based on mining locations

The clustering dendrogram using the complete agglomerative linkage determines each rock's properties' impact strength for their respective cluster. Table 7 shows the impact strength value of individual rock properties. In Table 7, cluster 1 refers to the mining areas 1, 2, 4, 5, 8 and 20. Also, cluster 2 refers to mining areas except 1, 2, 4, 5, and 8. The rock properties have a higher impact on drilling locations when its impact strength value is positive.

Table 7 Represents the impact strength of individual rock properties in different clusters

Clusters	*Dry-density*	*Porosity*	*CHI*	*BTS*
1	–1.1256113	1.4715033	–1.4966445	–1.3560117
2	0.2814028	–0.3678758	0.3741611	0.3390029
	Sonic velocity (P-wave)	*Young's modulus*	*CAI*	*UCS*
1	–1.2752952	–1.5023347	–0.5596735	–1.5025437
2	0.3188238	0.3755837	0.1399184	0.3756359

The clustering impact strength value for the rock properties associated with clusters 1 and 2 are shown in Table 7. The impact strength value for dry density, CHI, BTS, sonic velocity (P-wave), Young's modulus, CAI and UCS is negative in cluster 1. However, porosity has a positive value in cluster 1. It means that the rock properties such as dry density, CHI, BTS, sonic velocity (P-wave), Young's modulus, CAI and UCS are less significant to those sandstone block, which has been collected from mining areas 1, 2, 4, 5, 8, and 20. However, porosity greatly impacts the sandstone rock located in mining areas 1, 2, 4, 5, 8, and 20. In cluster 2, the impact strength value of rock properties such as dry density, CHI, BTS, sonic velocity (P-wave), Young's modulus, CAI, and UCS was found to be positive. At the same time, the impact strength value for porosity is negative in cluster 2. Thus, all the other rock properties, except porosity, have a high impact in cluster 2 and are more significant to the sandstone block. The summary of Table 7 here helps to understand the wear test experiments which are to be carried out by choosing the appropriate rock disc specimen based on the clustering results. Here, rock's strength is different for different clusters, which means that bit wear will always be a function of rock properties.

The problem statement in this research work is of classification type. Therefore, the Hierarchical agglomerative clustering method was used to fulfil the objective of this research. This method classifies different mining locations based on rock properties by considering various alternate agglomerative linkages such as average, complete, single, centroid, and median. Table 6 represents the clustering results obtained from various linkages. The quality of clustering has been verified by the silhouette method. The optimal number of clusters and the parameters, such as average silhouette width value are shown in Figure 6 and Figure 7, respectively. The results from Table 7 represent the impact strength of individual rock properties in their respective cluster. These strength values reflect the state of rock properties and help designers to prepare rock disc specimens for wear tests based on their research needs.

Laboratory tests like rotary wheel abrasion test, impact test, and micro-tribological test using pin-on-disc wear test apparatus (Angseryd et al., 2013; Konyashin and Ries, 2014) were conducted on rock samples to investigate the wear characteristics of inserts. These tests measure the wear rate in terms of the specimen's weight loss in defiance of sliding distance against the rock specimen. The studies conducted by Heinrichs et al. (2017) and Saai et al. (2020) state that the performance of inserts mainly depends on rock properties. Thus, it becomes essential to categorise the rock samples of different mining locations into clusters for the optimal judgement of rock during laboratory tests. The machine learning-based clustering approach significantly fulfils the objective by segregating rock samples from different mining locations into clusters. This approach also determines the impact strength of individual rock properties in the clusters. This information may be used for the selection of appropriate rock disc specimen in wear test setup, which may ultimately provide better solution for tool wear against the rock properties.

4.4 Primary limitations, broader applicability and the implications of findings

Some clustering algorithms are sensitive, provide incomprehensible results, and cannot filter the noisy data from the data set. Hierarchical-based clustering analysis in this study offers robust data interpretation. Rock is heterogeneous, and its properties vary from place to place. Hence, good scalability is needed to visualise rock data precisely, and Hierarchical clustering is the best approach to deal with these issues. The considered approach identifies the data pattern and carefully analyses the clustering quality. This clustering approach is reliable for dealing with low-and high-dimensional data and provides optimal results. It also detects the arbitrary shape of clustering, integrates hierarchical agglomeration for the rock data, and offers optimum results. The clustering results obtained in this study are interpretable, understandable, and usable. It opens a wide range of opportunities to interpret mining data from field studies. It provides better opportunities for drilling-related problems and multi-dimensional solutions in various areas, including designing experiments and selecting better tools under rock drilling.

5 Conclusions

Clustering analysis is a fast-growing application in data science, which works with a set of algorithms and delivers correct and precise information on a big data set without error. The study discoursed the following:

- The obtained rock properties have been examined using the hierarchical-based clustering approach, which determines the segregated groups of rock with similar traits. The R programming framework with R studio software was used in the study for accurate and faster calculation of the data gathered from a different source.
- In the study, this approach classifies the different rock properties based on their mining locations and determines the impact of each rock property in their groups.
- The results from the clustering analysis revealed that the 30 different mining locations considered in the study could be grouped into two clusters based on the similarities of rock properties. The information gathered in this study opens a discussion on selecting the appropriate rock and tool material to plan the experiments on wear test equipment in the laboratory.
- The study has offered an evaluative perspective of an essential industrial issue. This investigation delineated significant mining issues, such as choosing appropriate rock specimens for wear tests using the clustering approach. Further, this work enhances the specimen's perpetual quality in research facility tests for comparative sorts of rock information.
- The outcomes from cluster means and within the cluster sum of squares were conducive when the data was dissected with the silhouette method. The circumstances on an ideal number of clusters and their related outcomes by considering different agglomerative linkages were found reliable for the problem statement.

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The first and corresponding author has prepared the manuscript.

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