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Estimation of Button Bit Drillability Index on Granitic Rocks using their Mineralogy Composition and Rock Strength

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Abstract

This study focuses on predicting the drillability of granitic rocks—precisely the wear rate of button bits, by integrating rock strength and mineralogical properties. The objective is to develop a predictive model for bit wear rate using a Rock Engineering System (RES) approach. Key rock parameters (uniaxial compressive strength, porosity, specific gravity, and the mineral content of quartz, plagioclase, hornblende, and biotite) were analysed via a RES interaction matrix to derive a new Drillability Index capturing their combined influence. This analysis revealed that UCS and porosity are the most influential factors in the system. The resulting RES-based model correlates strongly with observed bit wear rates, achieving a high coefficient of determination ($R^2 \approx 0.93$) and low prediction errors (RMSE = 2.79, MAE = 2.14). The MAPE (= 38%) indicates a marked improvement in accuracy over traditional regression methods. Integrating mechanical and mineralogical factors is a novel approach to drillability prediction, providing a more comprehensive account of rock characteristics than conventional models. Validation results show that the RES-derived Drillability Index reliably predicts field performance, offering practical value for optimising drilling operations and guiding geomechanical analysis. Additionally, the study proposes a drillability classification scheme to further support the field application of the findings.

1. Introduction

Drilling is one of the most critical activities within mining, geotechnical engineering, and petroleum exploration due to its direct impact on excavation productivity, operational expenses, and equipment wear. The contribution of numerous elements, such as rock characteristics, drill bit selection, and drilling settings, determine the impact of drilling activities. The mechanisms of penetration, bit performance and energy consumption have been investigated previously [1-2], but they have reinforced the discrepancies in the interactions between geological and mechanical properties. The most significant factors affecting rock drillability, simply the ease of the rock being drilled, are rock strength, mineralogical composition, texture, and operational parameters during the drilling process [3-4]. In recent years, rock mechanical properties, including rock UCS, tensile strength, porosity, and specific gravity, which are considered significant in drillability, have been investigated [5]. There are several studies into the drillability index (DI), combining geomechanical properties and operational drilling parameters. A novel drillability index was developed based on 65 rock mass samples, which achieved an error range of ±7% in the penetration rate prediction [6]. Later, the researcher achieved a 94% effectiveness in evaluating carbide bit wear within rotary drilling procedures by employing digital-image processing technologies to assess drill bit wear. In a real-world application [7]. Another study on the effects of bit hardness, drilling machine parameters and rock mechanical properties on noise during hard rock drilling

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discovered that bit wear increases noise intensity by 21 per cent, making noise analysis a potential indirect indicator of bit deterioration [8].

Drillability prediction and bit wear analysis are critical to optimising the performance of drilling operations in mining and petroleum. Many studies are enhancing prediction precision through machine learning, empirical modelling, and experimental validation methods. The long Short-Term Memory (LSTM) model was used to evaluate bit wear predicting trends in Southwest Nigeria mines, and it achieved an accuracy of prediction up to 92.5% [2]. By leveraging real-time drilling data from 300 boreholes, their model achieved orders of magnitude improvement over conventional regression techniques. On the other hand, a study on extensive bit wear modelling based on 25 drilling operations concluded that bit degradation was highly correlated (R^2 = 0.89) to operational parameters such as rotary speed and thrust force [9]. Similarly, the prediction of optimal drilling rates using the Bourgoyne and Young model achieved a predictive accuracy of 93%, which is an improvement from the 82% completed using the traditional approach [10]. The introduction of the Rock Mass Drillability Index (RMDI) to estimate the drilling rates for open-pit mines resulted in a low prediction error, with a root mean square error of 1.85, while verifying its accuracy over 100 boreholes [11].

The physico-mechanical properties of rock formations directly impact drillability and bit wear. The strength of the rock is one of the most critical parameters for drilling because it is directly related to the amount of energy expended in penetrating the rock. Among the parameters studied for rock drillability, uniaxial compressive strength (UCS) is one of the most commonly tested and previous studies have strongly correlated it with penetration rate. Evidence has shown that increasing UCS (90.56–121.43 MPa) reduced the penetration rate with a 98.5% coefficient of determination, representing a strong inverse correlation [12]. A 95% inverse correlation on the UCS-penetration rate relationship further reinforces UCS as an essential parameter influencing drilling efficiency [13]. A polynomial model has demonstrated that UCS has a high precision for predictability of drill rates in underground mining with an R^2 of 0.92 [14]. A machine-learning approach to enhance penetration rate estimations reported that UCS complementary features improve drillability predictions more accurately [15]. More importantly, rocks with UCS > 150 MPa exhibited a much lower penetration rate, while UCS < 100 MPa eased the drilling [16]. Besides UCS, some other parameters have also been studied as determinants of drillability, especially Brazilian tensile strength (BTS) and point load strength index (PLI). BTS moderately correlates with penetration rate, particularly in fine-grained rocks where tensile failure mechanisms play a more significant role in drilling performance [17]. Conversely, the relationship between drilling-specific energy (DSE) and formation geomechanical properties in oil drilling applications reported a predictive correlation (R^2) of 0.88 [18]. In another significant study, a probabilistic ensemble learning model to assess penetration rates in multifaceted geological environments offered a 15% accuracy boost compared to traditional deterministic models [19]. These studies demonstrate a continuous comparison of data-driven methodologies against past drilling performances and the adoption of real-time operational parameters into prediction models for drill performance prediction.

Meanwhile, BTS and UCS data used as inputs to a fuzzy evaluation model obtained higher accuracy of classified drillabilities between lithologies [20]. An investigation of the influence of the porosity of rocks revealed that values exceeding 0.19 reduce drillability negatively, especially in sandstones, owing to the pore collapse and energy dissipation during the drilling [21]. The development of and combination of Composite Penetration Rate Index (CPRI) with UCS, BTS and porosity to estimate drillability in metamorphic rocks achieved R^2 of 0.92 [22]. However, studies have primarily emphasised individual strength parameters rather than their collective influence on drillability and wear rate of bits. Thus, including UCS and BTS, as well as porosity and specific gravity, into a single drillability index allows this study to provide a more holistic and pragmatic evaluation of drillability in rocks, advancing the field with a more integrated approach. A comparison of multiple scales of rock hardness revealed that penetration rate had the most significant correlation (R^2= 0.87) with Schmidt hammer hardness (SH) and Brazilian tensile strength (BTS) [23]. Further, micro-fabric analysis (such as grain size and interlocking texture) explains 30% of the variance in the drillability index (DI) across 120 rock samples [24]. In the same classification, the relationship between UCS (70–160 MPa) and porosity (1.2%–8.5%) values on horizontal drilling rates in marble quarries shows that the penetration rate decreases by 45% when the UCS values increase [25]. However, increased rock porosity helps to improve drilling efficiency.

Meanwhile, the study of pneumatic top hammer drills on five rock types using a laboratory-controlled experiment reported penetration rates of 2.5 m/min for high-strength granite and 10.8 m/min for soft limestone [26]. Moreover, an experimental drilling simulator used to examine drilled-cutting transport efficiency covering 35 test scenarios confirms that the optimal fluid viscosity lowers bit wear by 28% and enhances cutting transport efficiency by 37% under controlled operating regimes [27]. However, the mineralogical properties, especially the contents of quartz and feldspar, have been confirmed to be the main factors affecting drill bit wear and penetration efficiency [20-21].

Mineralogy is also vital in impacting drillability, as mineral hardness, grain size, and texture affect penetration rates and bit wear. One of the most complex particle forms is quartz, which has a high hardness (Mohs scale 7), greater abrasiveness, and incremental penetration of the bit wear. Lin & Kuangdi [1] showed that rocks containing >40% quartz produced much lower penetration rates and more wear on tungsten carbide drill bits than rocks with <40% quartz. Similarly, Wang et al. [20] utilised a two-layer fuzzy evaluation model and found quartz and iron content to be the most dominant parameters affecting drillability. Chen et al. [21] explored the impact of porosity, permeability, and mineralogical composition on drillability, reporting an exponential decrease between porosity and drillability post-0.19 due to drill-induced energy absorption and the collapsing of pores. Also, Srivastava and Vemavarapu [22] developed the Composite Penetration Rate Index (CPRI) with mineralogical properties included in the drillability assessment, which reached a predictive accuracy of $R^2 = 0.92$ in metamorphic rocks. Intensifying drillability in terms of the mineral content has been discussed in the literature, and previous studies related to mineralogical contents, mainly feldspar and biotite contents, have interpreted that feldspar acts to increase rock strength. However, with its platy cleavage structure, biotite increases the weakness of the rock matrix, thereby hindering drillability. Because of their weak and laminated structures, biotite-rich rocks require lower specific energy in the drilling [28]. These findings have resulted in the development of many predictive models to improve the accuracy of drillability prediction, such as empirical equations, machine learning models, and hybrid methods [26-28]. Unfortunately, these studies do not provide a comprehensive framework incorporating rock strength, mineralogical properties, and bit wear rate under the same spectrum. While numerous studies are dedicated to predicting penetration rate, most neglect the multi-parametric impact of rock properties on drilling efficiency.

Recent progress in machine learning and artificial intelligence (AI) have improved drillability predictions significantly. The prediction of penetration rates using deep learning and ANNs had high accuracy for complex geological conditions [17, 29]. Meanwhile, deep learning models have been used to combine rock properties as input features to quantitatively predict the mineralogical and mechanical properties of rock mass [15]. A hybrid machine learning model has been used to enhance rate of penetration (ROP) predictions by accounting for mechanical properties and drilling parameters [30]. Another approach is implementing Monte Carlo simulations [7] and stochastic modelling [31] to put an uncertainty value on drillability predictions. In carbonate reservoirs, the models used were based on support vector machines and decision tree models to optimise penetration rate and torque on a bit [28]. This approach showed an improvement in accuracy of 15–20% compared to conventional empirical methods. However, many of these models still rely heavily on local datasets, hindering their application across different rock formations. Machine learning has gained momentum in drillability studies and has achieved higher accuracy and efficiency in prediction. K-Nearest Neighbors (KNN) and Multi-layer Perceptron (MLP) models have also been used to predict the rate of penetration (ROP) of oil and gas wells, obtaining R^2 values of 0.92 and 0.94, respectively [32]. This study addressed the pros of

AI models in capturing non-linear geological changes. Meanwhile, automated image processing techniques have been used to evaluate cemented carbide bit wear and reduce manual error rates from traditional assessment techniques by 35% [7]. This evolution is a clear trajectory from associatively regular models to perceptually intelligent ones that can handle complex datasets to predict penetration rates and wear on the lateral bits more accurately.

The Rock Engineering System (RES) approach addresses several civil engineering challenges. The RES has been used extensively to formulate an assessment framework for rock mass blastability [33] and define environmental risk criteria for reservoir pollution. [34] In the same way, it has been employed for radioactive waste management, applied in safety factor prediction of circular failure [35], investigation of traffic-induced air pollution [37], and prediction of tunnel boring machine (TBM) penetration rates [38]. In this respect, researchers have used RES to assess the risk of spontaneous coal combustion [39] and predict powder factors from rock mass and geometric parameters [40]. Additional applications are related to rock mass classification [41] and flyrock distance prediction in surface blasting [42]. Moreover, it was used to develop a model for predicting blast-induced peak particle velocity (PPV) [43]. One such prominent work designed a predictive model for iron ore oxides' rotary abrasion penetration rate [44]. The authors applied the RES methodology and achieved R^2 of 0.91 when relating the penetration rate with the bit wear, rock properties and drilling parameters [44]. However, no study has used RES for fragmentation prediction or considered the interaction between controllable and uncontrollable parameters and how these affect blast outcomes in various geological domains.

Although significant efforts have been made to predict penetration rates and assess drillability, little has been done to investigate the multi-interaction impact of rock strength and mineralogical composition on the bit wear rate. Despite recent advancements, most studies concentrate on the individual implications of mineralogical inputs independently of their cumulated effects and their possible interaction with rock mechanical properties. Most models' approaches are empirical and/or semi-empirical and thus static regarding geology. In addition, UCS has been the only parameter analysed to predict parameters and their effect on bit wear and overall drillability. The goal of this study is to fill this gap by developing a holistic drillability index (DI) that integrates quantitative values for quartz, plagioclase, hornblende, and biotite in the understanding of the efficiency of rock drilling, which involves the formation of a ground drillability index suitable for practical application in the field. This study proposes a Rock Engineering System (RES)–based drillability index to overcome these challenges and increase predictive capability associated with different geological conditions.

2. Methods

2.1. The Study Areas

The scope of this study is based on the south-western Nigerian Basement Complex (latitudes 7˚00'00" to 8˚00'00" N and longitudes 3˚00'00" to 5˚00'00" E), which has a wide variety of Precambrian rocks [45]. The Migmatite-Gneiss Complex, meta-sedimentary sequences, and the Pan-African granitoids [46] mainly make up this section. The first is the Migmatite-Gneiss Complex, which is composed of predominantly migmatites, banded gneisses and granite gneisses. These rocks show structural heterogeneities expressed by dominant N-S and NNE-SSW trending foliations and lineaments, indicative of several deformation episodes [46]. The gneissic terrains are interspersed with meta-sedimentary sequences, primarily schist and quartzite, which reflect low to medium-grade metamorphism characteristic of the green schist faces. These older units are intruded by the Pan-African granitoids (locally called "Older Granites"), which comprise granites, syenites and diorites that were emplaced during the Pan-African orogeny (about 600 million years ago) [47]. These formations have different physico-mechanical properties, making them suitable for construction and engineering. The mineralogical composition of rocks here in the complex, density variations, low porosity and high durability within the rock units [46] is attested to by studies of the Precambrian basement rocks. The Unconfined Compressive Strength (UCS) is in the order of 82.50 to 228.50 MPa, indicating that these rocks have moderate to high strength and can be used for various engineering purposes [40, 49]. The Basement Complex rocks cover almost 100% of the total land surface area of Oyo State [50]. The geological map of the study area is in Figure 1.

2.2. Data Collection

Two hundred and forty (240) drilling activities (30 in each location) were monitored to record the penetration rate and bit wear in eight selected quarries around Oyo State, Nigeria. Forty-five samples of granitic lumps were collected from the benches in the quarry for laboratory analysis. The systematic methodology outlined in the flowchart in Figure 2 begins with field investigation and data collection and branches out to field monitoring and laboratory testing. Field monitoring was used to estimate penetration rates, while laboratory testing was used to determine rock properties (UCS, Sp, n) and mineralogical properties (Q, H, P, B). The data collected was then analysed through a Rock Engineering System (RES) approach to calculate the bits' drillability index (DI). Overall, these analyses culminate into model evaluation, resulting in two components—one for RES Model Development and one for Regression; together, the two allow for model evaluation across this multi-faceted process.

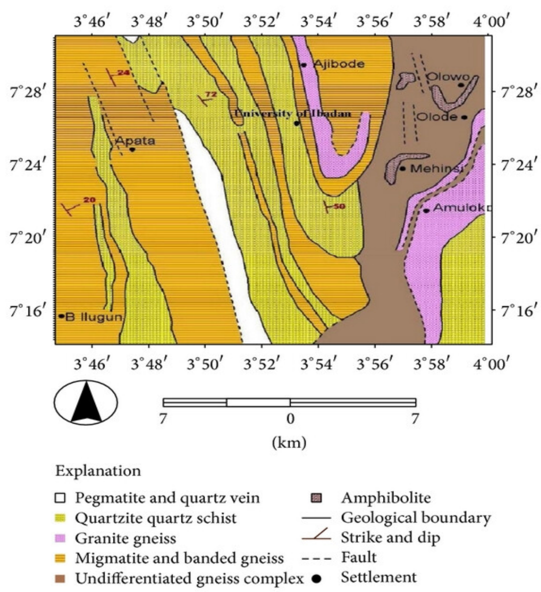

Figure 1. The Geology of Oyo State [51]

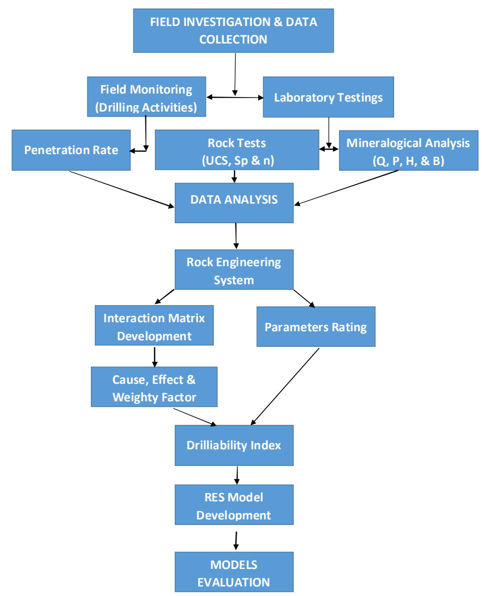

Figure 2. The Flowchart of the Research Process

2.3. Estimation of Rock Mechanical Properties

The rock mechanical properties investigated in this study are the uniaxial compressive strength (UCS), Specific gravity (Sp) and porosity (n) were evaluated according to the standard and procedure of the International Society of Rock Mechanics [52]. Accordingly, UCS, Sp, and n were estimated using Equations 1 to 3.

$$C_o = \frac{P}{A} = \frac{4P}{\pi D^2} \tag{1}$$

$$G_s = \frac{M_s}{M_w} \tag{2}$$

$$n = \frac{M_{sat} - M_s}{V} \times 100 \tag{3}$$

Where C_o is the UCS (MPa), P is the applied peak load (kN), D is the diameter of the sample (m) and, A is the cross-sectional area of the sample (m^2), M_s is the mass of the sample and M_w is the mass of water displaced, n is porosity (%), V is the bulk volume (cm^3), M_{sat} is the saturated surface dry mass (g) and M_s is the mass of the sample after oven-dried (g).

2.4. The Mineralogy Component

This study exposed the selected rock samples to optical analysis and determined modes by counting points through Swift Model E equipment with an automated stage fitting device. A thin section of samples prepared for microprobe analysis was examined. The samples were prepared in about 30 mm x 40 mm, and the total counts were from 1500 to 2000 for individual samples. This test was conducted by covering the entire surface of the thin section. Minerals counted were quartz, plagioclase, hornblende, biotite, and accessory minerals.

2.5. Penetration and Wear Rate

The performance of the drilling bits was evaluated by measuring their penetration rates using Equation 4. The drilling performance was evaluated using the same bits diameter, feed pressure, rotation pressure and speed, low pressure, air pressure, and drill-hole length (8 m). A series of drilling experiments were performed, during which the wear rate was measured for the drilling bits at regular intervals using Equation 5. The mass loss method measured the abrasiveness and wear rate of the drilling bits by weighing them before and after the drill bit reached a depth of 8 m. A digital weighing balance was used to measure the bit weight, with a resolution of 0.1 g [53]. Most losses would occur at the bit matrix and cutter head because both will be exposed to the rock [54].

$$Pr = \frac{DD}{T} \quad (4)$$

$$W_r = \frac{W_L}{T} \quad (5)$$

Where Pr is the penetration rate (m/s), DD is the drilling depth measured in meter and T (seconds) is the time taken to drill to the measured depth, Wr is the wear rate (mg/s), W_L is weight loss (g) and T is the drilling time (s).

2.6. Rock Engineering System for Drilliability Index

The rock engineering system is a powerful tool introduced by Hudson [55] for characterising effective parameters in rock engineering problems [54]. The RES method can handle multi-variable and non-linear interactions of rock properties, making it a desirable tool for solving rock engineering problems, such as Drilliability. Notably, the RES approach can model the asymmetric nature of rock mass to precisely evaluate rock properties and non-numeric parameters that significantly influence its engineering applicability [55-56]. Three main steps were involved in developing the RES-based bits efficiency evaluation. They identify parameters that influence risk incidences in rock drilling, investigate their pattern of interactions to evaluate the significance (weighty factor) of each parameter in the overall risk conditions and estimate the corresponding Reliability index (DI). Parameters identified by literature to influence drilling efficiency were evaluated and recorded. The inter-relationship among uniaxial compressive strength, specific gravity, porosity, mineralogical composition and penetration rate was used to determine the Drilliability index, which explains its efficiency. The wear rate was correlated with the Drilliability index to develop a model for predicting bit efficiency.

2.6.1. Interaction Matrix

The critical component of the RES is the interaction matrix, which describes the relationship between perpendicular parameters and summarises the influence of all the parameters using the cause, effect and weighty factor. The matrix constructed to evaluate the interaction of parameters in the RES is such that parameters identified to influence the parameter under investigation are lined along the central diagonal. The coding for a parameter's influence level on others is computed in the matrix table along their perpendicular cells. Figure 3 (a & b) shows how two and multiple-parameter relationships are arranged in the interaction matrix table, respectively. The ESQ coding approach was adopted in this study to evaluate the relationship between the parameters [55]. In the ESQ coding approach, the interaction degrees are coded 0, 1, 2, 3, 4, and 5, which indicate no, weak, medium-strong and critical interactions, respectively (Table 1) [55]. The programming of parameters' interaction in the matrix table is done by computing the value that matches the influence of the relationship of two in their adjacent cells. The developed matrix for the relationship between parameters influencing bit drillability is in Figure 3.

Table 1. ESQ interaction coding method [55]

Coding	Description
0	No interaction
1	Weak interaction
2	Medium interaction
3	Strong interaction
4	Critical interaction

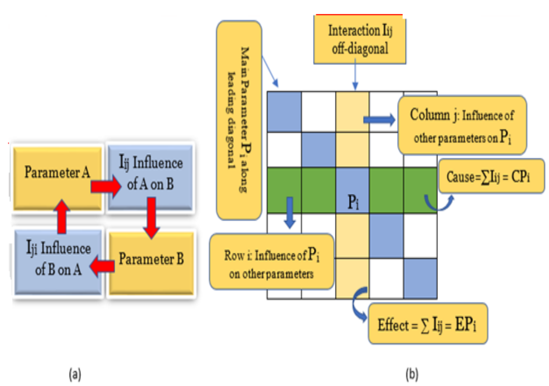

Figure 3. Interaction Matrix with (a) Two Parameters (b) Multiple Parameters [55].

2.6.2. Estimation of the Weighty Factor

The two-way relationship of the parameters, the value of the horizontal and vertical addition of the coding values for individual parameters in the matrix, is referred to as the Cause (C*i*) and Effect (E*i*), respectively (Equations 6–7). The summation and difference of the value of the Cause and Effect of individual parameters estimated in the interaction table are known as the interaction intensity and dominance of the matrix system, respectively. The significance of each parameter is often determined by plotting the coordinate of Effect against Cause. Equal values of the Cause and Effect are lined on the diagonal centre of the Cause and Effect plot in the figure. It indicates the point of equilibrium between dominance and subordination. Likewise, those parameters that fall on the left side of the equilibrium points are the subordinate parameters in the matrix system, while those on the left side are the dominant. The influence of individual parameters in the interaction table is estimated using the percentage factor, known as the weighty factor (αi), and the estimation formula is in Equation 8 [55-56, 58-59]. The results of the weighty factor are in Table 4.

$$C_{pi} = \sum_{j=1}^{n} I_{ij} \tag{6}$$

$$E_{pj} = \sum_{i=1}^{n} I_{ij} \tag{7}$$

$$\alpha_i = \frac{(C_i + E_i)}{(\sum_i C_i + \sum_i E_i)} \times 100 \tag{8}$$

where C_i is the cause of the *i*th parameter, E_i is the effect of the *i*th parameter.

2.6.3. Estimation of Drilliability Index

The RES approach for estimating the drillability index was adopted from literature [4, 40, 42-43, 58], where the approach was used to estimate indexes to solve rock engineering problems. This concept was first introduced to estimate rock fragmentation's vulnerability index (VI) and identify vulnerable areas in tunnelling operations [58]. Applying the RES approach to drilling bit selection involves considering poor penetration rate and increased wear index risks in drilling operations [4, 40, 43]. The variations in DI were the basis for determining the level of risk and were estimated in this study using Equation 9. The classification of DI is divided into three main categories with different severity on the normalized scale of 0–100, as shown in Table 6, while the results for the estimated drillability index are in Table 7.

$$DI = 100 - \sum_{i=1} \alpha_i \frac{Q_i}{Q_{max}} \tag{9}$$

where Q_i and Q_{max} are the value (rating) of the ith parameter, and the maximum value assigned for the ith parameter (normalization factor), respectively.

3. Results and Discussion

Critical parameters associated with rock drillability and bit wear rates are summarized in Table 2 based on the study results. The UCS varied between 137.23 and 162.8 MPa, demonstrating the high strength of the rock. The estimated penetrated rate recorded was between 2.37 and 2.80 m/min, while the wear rate was 0.000292 to 0.00305 g/s. The specific gravity of the rock had a value between 2.40 and 3.20, and the porosity was between 1.20 and 2.50%. These results were compared with earlier studies conducted in the geological basement of South-western Nigeria, where similar trends were observed with high UCS, moderate penetration rates and low-to-moderate wear rates [1-2]. However, minor value variations can be limited to geological heterogeneities like changes in mineralogy and grain size and structural discontinuities, which draw attention to the need for localized studies for accurate drilling performance prediction.

Table 2. Data Characteristics

No	Parameter	Unit	Symbol	Min	Max
1	UCS	MPa	UCS	137.23	162.8
2	Quartz	%	Q	40	49
3	Plagioclase	%	P	21	28
4	Hornblende	%	H	4	9
5	Biotite	%	B	7	21
6	Penetration Rate	m/min	P_r	2.37	2.80
7	Specific Gravity	-	S_P	2.40	3.20
8	Porosity	%	n	1.20	2.50
9	Wear Rate	g/s	W_r	0.000292	0.00305

3.1. Analysis of the Interaction between Parameters that Influence Bit Wear Rate

Table 3 presents the coded interaction matrix of variables under investigation, and the results used for the cause-effect analysis are presented in Table 4. Cause (C) and Effect (E) represent the significance and influence of each parameter in the matrix [54]. The degree of dominance of each parameter in the interaction matrix is the difference in their Cause and Effect (C-E). It can be inferred from Table 4 that Quartz (Q) and Plagioclase (P) recorded the highest positive values of dominance (20 and 14, respectively), indicating that they are strong drivers in the matrix system. Meanwhile, the penetration rate (Pr), uniaxial compressive strength (UCS), porosity (n), and specific gravity (Sp) showed negative (C–E) values. The interpretation is that these are sensitive or dependent (with high Effect values) parameters strongly regulated by mineralogical composition. In particular, Pr recorded the highest negative value of -23 for the degree of dominance, indicating the most susceptible to influence from other variables. Therefore, it is proper to suggest that the high interaction values obtained for these variables correlate with the abrasive characteristics of these minerals, which seem to impact drill-bit wear significantly. Moreover, the intensity rating for the individual parameter in the interaction matrix is the addition of the coded values for cause and effect (C+E). In Table 4, UCS and porosity had the highest intensity rating of 24, indicating their total interactivity. Consequently, both tables point to Quartz and Plagioclase as major contributors to drilling behaviour. However, UCS, porosity and penetration rate show strong sensitivity, highlighting the interconnected nature of rock properties and their joint relationships to drilling performance and bit wear.

Table 3. Interaction Matrix for Factors Affecting Wear Rate

UCS	0	0	0	0	4	0	2
4	**Q**	2	2	2	4	4	2
3	0	**P**	2	2	3	3	3
2	0	0	**H**	2	4	1	2
3	0	0	2	**B**	2	2	3
0	0	0	0	0	$\mathbf{P_r}$	0	0
3	0	0	0	0	3	$\mathbf{S_p}$	3
3	0	0	0	0	3	3	**n**

Table 4. The weighting factor of the parameters

Parameter	Cause (C)	Effect (E)	C-E	C+E	α_{ij}
UCS	6	18	-12	24	14.46
Q	20	0	20	20	12.05
P	16	2	14	18	10.84
H	11	6	5	17	10.24
B	12	6	6	18	10.84
P_r	0	23	-23	23	13.86
S_p	9	13	-4	22	13.25
n	9	15	-6	24	14.46
Total	**83**	**83**	**0**	**166**	**100**

3.2. Cause-Effect Analysis

The Cause-Effect diagram in Figure 4 shows a polling interdependency relationship among rock Drilliability parameters. Quartz (Q), Plagioclase (P), Biotite (B), and Hornblende (H) emerged as important (Cause) parameters in terms of their significant Effect on wear rate and penetration efficiency. In contrast, penetration rate (Pr), uniaxial compressive strength (UCS), porosity (n), and specific gravity (Sp) were parameters more sensitive to Effect, and their response was mineralogical composition dependent. This behaviour is comparable to previous studies that showed that mechanical behaviour during drilling was dominated by rock mineralogy. Similar relationships was described by previous researchers, noting that Quartz was a key factor influencing the drill-bit wear because of its abrasive characteristics [1]. Penetration rate relates significantly to rock strength and porosity, as increased UCS values usually decrease the drilling efficiency [2]. The current findings confirm these interactions, suggesting the need for integrated mineralogical and mechanical analyses to predict drilling performance in geological basement complexes accurately.

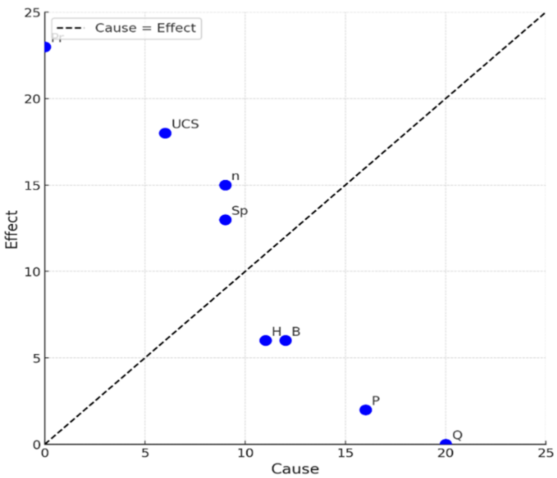

Figure 4. Cause-Effect Diagram

3.3. Rating of parameters

Parameters considered for this study were rated based on their general classification system, and coding was assigned depending on how they influenced the drill wear rate. The ESQ coding classification is divided into five groups, with values ranging from 0 to 4. Zero represents the worst scenario of the influence of such a parameter on drillability, while four is the best. Zero means poor effect or unfavourable condition, and 4 implies the most favourable condition. Table 5 presents the rating of the parameter used in this study. The ratings were in accordance with previous studies employing RES solutions and vetted by three professionals in the field of rock drilling [4, 40, 43].

Table 5. Ratings for parameters influencing DI

Parameters	Symbol	Values and Ratings						
Uniaxial Compressive Strength	UCS (MPa)	Value	<25	25 – 50	51 – 100	101 – 250	>250	
		Rating	4	3	2	1	0	
Quartz	Q (%)	Value	<20	20-40	40-60	60-80	80-100	
		Rating	4	3	2	1	0	
Plagioclase	P (%)	Value	<20	20-40	40-60	60-80	80-100	
		Rating	0	1	2	3	4	
Hornblende	H (%)	Value	<20	20-40	40-60	60-80	80-100	
		Rating	4	3	2	1	0	
Biotite	B (%)	Value	<20	20-40	40-60	60-80	80-100	
		Rating	0	1	2	3	4	
Penetration Rate	P_r (m/min)	Value	<0.2	0.2-0.24	0.24-0.26	0.26-0.28	0.28-3.0	>3.0
		Rating	5	4	3	2	1	0
	S_p	Value	<2.0	2.0-2.5	2.5-3.0	>3.0		
		Rating	3	2	1	0		
Porosity	n (%)	Value	<1.5	1.5-2.5	2.5-3.5	>3.5		
		Rating	0	1	2	3		

3.4. Drilliability Index Classification and Its Implications for Rock Drilling Performance

The classification, as well as the calculation of the Drilliability Index (DI), is presented in Tables 6 and 7, which also emphasize the importance of DI in terms of classifying drilling risk as very low (0-20), low (20-40), medium (40-60), high (60-80), and very high (80-100) [4, 40, 43]. Table 7 calculates DI for a button bit, which creates values ranging from 45.25 to 50.88, representing the medium drillability category (III). Such DI values indicate moderate drilling difficulties, which can be expected for moderately abrasive and hard rocks. Similar classifications had been reported in previous studies undertaken in geological basement complexes like those in Southwestern Nigeria [2]. The mechanical testing for DI of diorite found similar DI values, which were reported as medium to high, consistent with quartz-rich rocks' abrasive nature. Moreover, further supporting these findings, moderate penetration and wear rates were related to moderate DI levels at intermediate DI levels [2]. As a result, the current DI classification correlates with previous research, confirming its legitimacy as a drilling performance predictor and can serve as a practical guide for drilling planning and optimisation.

Table 6. Classification of Drillability Index

Risk Description	Very Low	Low	Medium	High	Very High
Category	I	II	III	IV	V
DI	0 – 20	20-40	40 – 60	60– 80	80-100

Table 7. Estimated Drilliability Index (DI) for the Button Bit

Parameter	UCS	Q	P	H	B	P_r	S_p	n	DI	Wr B
α	14.46	12.05	10.84	10.24	10.84	13.86	13.25	14.46		
Q_{max}	4	4	4	4	4	5	3	3		
1	1	2	0	4	1	2	1	1	50.01	14.869
2	1	2	1	4	1	1	0	3	45.25	30.500
3	1	2	1	4	1	1	1	1	50.47	3.000
4	1	2	1	4	0	2	1	2	45.48	30.357
5	1	2	1	3	0	3	1	1	50.41	4.476
6	1	2	1	4	1	1	2	0	50.88	2.923
7	1	2	1	4	0	2	1	1	50.30	8.915
8	1	2	1	4	0	2	1	1	50.30	8.261

3.5. Model for the Prediction of Drillability Index using Bit Wear Rate

The estimated drillability index was correlated linearly with the measured wear rate, and the results show that the drillability index decreases as the wear rate increases (Figure 5). This finding indicates that the drillability index measures the ease of drilling and that the wearing rate of bits is essential in determining the success of drilling operations. Also, a linear regression analysis between the drillability index and wear rate was used to develop a model for the button-bit wear rate, which is presented in Equation 9. The variance analysis of the model shows that it is statistically significant with a p-value <0.05 and a coefficient of determination of 0.933, indicating a strong relationship between the two parameters, and only 0.067% of the variance in wear rate that the drillability index cannot explain. Similarly, the model was used to predict the wear rate for the drilling bits, and the results were correlated with the measured wear rate. The results show a positive linear relationship between the predicted and the measured wear rate (Figure 6) with the r-square value of 0.933.

$$W_r = -4.7387(DI) + 245.75 \quad (10)$$

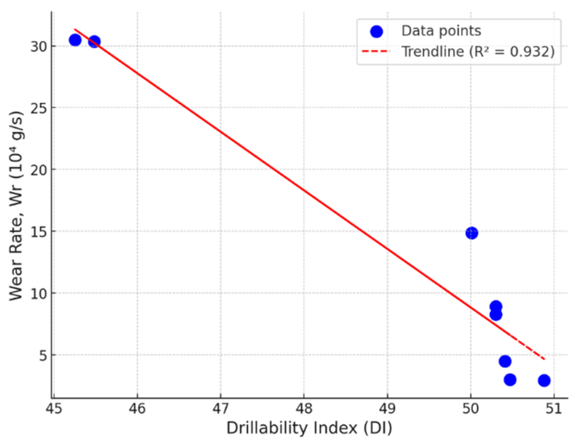

Figure 5. Wear Rate against Drilliability Index for Button Bit

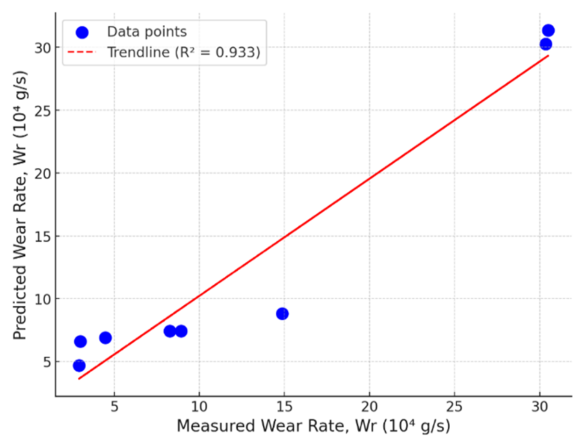

Figure 6. Relationship between Predicted and Measured Wear Rate

3.6. Model Performance Analysis

This study employed two approaches to evaluate the developed RES DI model. The first approach is the estimation of DI using multivariable regression analysis, and the results are compared using error analysis. Multicollinearity analysis of the prediction variables using the Variance Inflation Factor (VIF) was done using Equation 11. UCS and penetration rate exhibit severe multicollinearity and were removed. The multiple regression model is presented in Equation 12. The regression model's variance analysis shows that the coefficient of determination (R^2) is 0.8523, and the model is significant at 0.00253. Figure 7 compares the RES and regression predicted values with the measure bit wear and shows how closely each model matches actual values, identifying where deviations occur. The RES model more closely represents measured values, whereas the regression model has more variation at lower values.

$$VIF = \frac{1}{1 - R_i} \tag{11}$$

$$W_r = 1.43n - 2.14Q + 87.81S_P - 1.38P - 5.80H - 0.96B - 47.784 \tag{12}$$

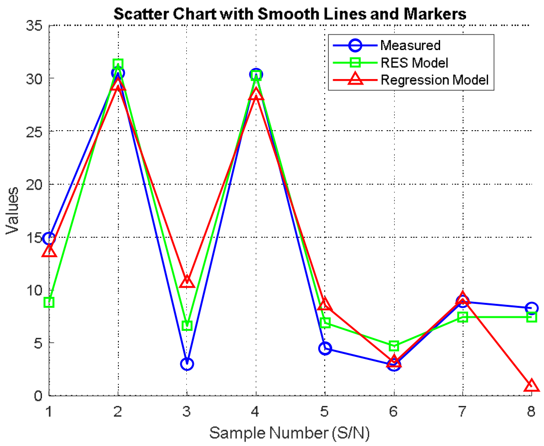

Figure 7. Comparison of RES and Regression Predictions with the Measured Bit Wear

4. Error Analysis

The accuracy of the developed models and their goodness of fit were then assessed by statistical measures like mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Theoretically, a predictive model is considered exceptional when RMSE is 0, R^2 is 1, MAE is o and MAPE is 0%. The formula for estimating MAPE, RMSE, and MAE are presented in Equations 13-15, respectively. As shown in Table 8, the RES Model outperforms the Regression Model in terms of MAE (2.14 compared to 3.00) and RMSE (2.79 compared to 4.13), signifying improved predictive accuracy. The RES Model's MAPE is 38.17%, while the Regression Model's is 57.87%, which makes RES more reliable. Both models, however, illustrate that there is scope to optimise further and reduce prediction errors.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_{i\,(mesured)} - X_{i\,(predicted)}}{X_{i\,(measured)}}\right) \times 100 \tag{13}$$

$$RMSE(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{i\,(measured)} - X_{i\,(predicted)}\right)^2} \tag{14}$$

$$MAE = \frac{1}{n}\sum_{i-1}^{n}\left(X_{i\,(measured)} - X_{i\,(predicted)}\right) \tag{15}$$

where $X_{i\,(measured)}$, $X_{i\,(predicted)}$, $\ddot{X}_{i\,(measured)}$, $\ddot{X}_{i\,(predicted)}$ and n are the measured, predicted, mean of measured and mean of predicted variables respectively, whilst n is the number of observations.

Table 8. Model Error Metrics Comparison

Model	R^2	MAE	RMSE	MAPE (%)
RES Model	0.9327	2.14	2.79	38.17
Regression Model	0.8523	3.00	4.13	57.87

5. Conclusions

This study used a Rock Engineering System (RES) approach to integrate multiple rock properties and successfully predict drill bit wear in granitic rocks. The key influences on wear were quantified by constructing an interaction matrix with mechanical (e.g., uniaxial compressive strength, porosity) and mineralogical (quartz, plagioclase, hornblende, biotite) parameters. All factors had notable impacts, with uniaxial compressive strength and porosity emerging as the most dominant (~14.5% each). This multi-factor analysis led to a drillability index correlating strongly with observed bit wear rates ($R^2 = 0.933$), confirming that lower wear corresponds to higher drilling efficiency. The results highlight the effectiveness of the RES methodology in capturing complex interactions. This contribution demonstrates how multi-parameter rock characteristics can collectively determine drilling performance and improve operational efficiency and drilling economics.

One of the strengths of this study is its comprehensive, systematic approach. The RES framework allowed the incorporation of virtually unlimited parameters, complemented by extensive field and laboratory data (240 drilling records from eight quarries and 45 rock samples to ensure robust model development. This integrated strategy yielded a reliable predictive model for bit wear and introduced a new classification system for rock drillability, guiding bit selection and drilling optimization. However, the findings are constrained by the study's scope: the model is calibrated for specific granitic rocks and mineral compositions, which may limit its generalizability to other settings. Additionally, as an expert-driven methodology, the RES approach relies on the quality of expert judgment in defining interaction matrices, potentially introducing some subjectivity. Future research should validate and refine the model across diverse rock types and mineral assemblages and incorporate additional drilling parameters to broaden its applicability. Such efforts would extend this work's contributions and further establish RES as a versatile tool in rock engineering practice. Furthermore, the influence of other factors such as discontinuities, drill type, and operator experience on penetration rate should be considered important for future research.

Declaration of interest

Authors declare that they have no known competing financial interest of personal relationships that could have appeared to influence the report in this paper.

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تخمین شاخص قابلیت حفاری با مته دکمه‌ای روی سنگ‌های گرانیتی با استفاده از ترکیب کانی‌شناسی و مقاومت سنگ

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چکیده:

این مطالعه بر پیش‌بینی قابلیت حفاری سنگ‌های گرانیتی - دقیقاً نرخ سایش مته‌های دکمه‌ای - با ادغام مقاومت سنگ و خواص کانی‌شناسی تمرکز دارد. هدف، توسعه یک مدل پیش‌بینی‌کننده برای نرخ سایش مته با استفاده از رویکرد سیستم مهندسی سنگ (RES) است. پارامترهای کلیدی سنگ (مقاومت فشاری تک‌محوری، تخلخل، وزن مخصوص و محتوای معدنی کوارتز، پلاژیوکلاز، هورنبلند و بیوتیت) از طریق یک ماتریس برهمکنش RES تجزیه و تحلیل شدند تا یک شاخص قابلیت حفاری جدید که تأثیر ترکیبی آنها را ثبت می‌کند، استخراج شود. این تجزیه و تحلیل نشان داد که UCS و تخلخل تأثیرگذارترین عوامل در سیستم هستند. مدل حاصل مبتنی بر RES به شدت با نرخ سایش مته مشاهده شده همبستگی دارد و به ضریب تعیین بالا ($R^2 \approx 0.93$) و خطاهای پیش‌بینی پایین ($RMSE = 2.79$، $MAE = 2.14$) دست می‌یابد. MAPE (= ۳.۸٪) نشان دهنده بهبود قابل توجه در دقت نسبت به روش‌های رگرسیون سنتی است. ادغام عوامل مکانیکی و کانی‌شناسی، رویکردی نوین برای پیش‌بینی قابلیت حفاری است که در مقایسه با مدل‌های مرسوم، شرح جامع‌تری از ویژگی‌های سنگ ارائه می‌دهد. نتایج اعتبارسنجی نشان می‌دهد که شاخص قابلیت حفاری مشتق‌شده از RES، عملکرد میدانی را به طور قابل اعتمادی پیش‌بینی می‌کند و ارزش عملی برای بهینه‌سازی عملیات حفاری و هدایت تحلیل‌های ژئومکانیکی ارائه می‌دهد. علاوه بر این، این مطالعه یک طرح طبقه‌بندی قابلیت حفاری را برای پشتیبانی بیشتر از کاربرد میدانی یافته‌ها پیشنهاد می‌کند.

کلمات کلیدی: شاخص قابلیت حفاری، نرخ نفوذ، نرخ سایش، RES، مته.