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Research paper

Prediction of physico-mechanical properties of rocks using dominant frequency of vibration during rotary drilling

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Abstract

In this study, an attempt is made to estimate some of the important physico-mechanical properties of sedimentary rocks using second-order multiple regression mathematical models. For model development, different drilling operational parameters and equivalent dominant frequencies of vibration excited at spindle head during rotary drilling were used. The prediction capacity or performance of the developed models was evaluated by using variance account for (VAF), root mean square error (RMSE) and mean absolute percentage error (MAPE).In addition, the strength of the relationship between measured and predicted value of rock properties are also checked using the Pearson correlation coefficient. Prediction performance indicators and correlation coefficients showed that the prediction model developed through the approached method can be successfully used for preliminary investigation of physico-mechanical properties of rocks which are often used as a primary data for the design of mining and civil engineering projects.

Keywords: *Rotary Drilling; Dominant Frequency of Vibration; Physico-Mechanical Properties; Multiple- Regression Modeling; Prediction Performance*.

1. Introduction

The physico-mechanical properties of rocks like uniaxial compressive strength (UCS), Brazilian tensile strength (BTS) and density are often needed for preliminary studies of rock engineering projects [1–3]. Similarly, during exploration drilling, a hard rock may be encountered about which there will be no information beforehand. In this condition, the estimation of rock properties could take some time [4–5]. There are several methods available in rock mechanics laboratory to measure the rock properties. However, the measurement of rock properties in the laboratory is expensive, time-consuming and often high-quality core specimens are needed for the test. It is not always possible to obtain the sufficient amount of high quality drilled cores from weak, highly fractured, weathered and thin layers of the rock matrix. Therefore, the engineers and geologists have been attracted to quantify the rock strength indirectly through the use of predictive models [6-13].
Many researchers investigated the rock strength properties by index method [14–20]. But, quality core specimens are required to conduct some of the index tests like point load index, P-wave velocity etc. The prediction of rock properties and geological conditions could be possible using measurement while drilling (MWD) data [21–27]. The prediction of rock properties during drilling were also carried out by many researchers through conventional methods. During a rock drilling, Schmidt [28] found a strong relationship between the penetration rate of the drill bit and UCS, density, tensile strength, and Young’s modulus. Kahraman [29] investigated the influence of operational parameter and rock properties on penetration rate during rotary blast hole drills and concluded that thrust on the drill bit, rotational speed, drill bit diameter and UCS of rocks are significantly influencing the penetration rate. Li and Itakura [30] proposed a model to relate the rock properties with bit shapes and drilling parameters. It was found that the UCS can be correlated well with the torque and penetration rate. Basarir and Karpuz [3] established the relationship to predict the rock mass strength using operational parameters of diamond bit drilling and equivalent penetration rate and reported that the approach is very useful for preliminary investigation of mining engineering projects. Vardhan et al. [31] attempted to investigate the rock properties based on the noise level produced due to the interaction between the drill bit and rock during drilling. It was concluded that there is a positive linear relationship between the uniaxial compressive strength of rock and noise level. An attempt was made by Rajesh et al. [32] to predict the rock properties through noise level produced during drilling and suggested to use the frequency of sound for estimation of rock properties in future work. The study on identification of rocks based on acoustic signal parameter gathered during rock drilling was made by the Zborovjan et al. [33] and Miklusova et al. [34]. It was concluded that the analysis of frequency component of the acoustic signal is useful for identification of rock type and controlling the rock disintegration process. Some of the studies proposed to utilize the acoustic signal generating during the drilling to investigate the rock formation around an oil well [35]. An attempt was made by Rostami and Kharaman [36] to detect the voids in rocks during drilling using the vibration data acquired at drill head. Mowrey et al. [37] reported on the use of adaptive signal discrimination (ASD) systems to assess the variations between the cutting of coal and cutting of mine rock. It was found that the basic character of vibrations of the cutter induced by cutting of coal appeared different from those induced by the cutting of shale or sandstone. Gradl

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et al. [38] attempted to trace the acoustical characteristics of the drill bit during drilling. The frequency spectra of recorded data were extracted by using Fast Fourier Transformation (FFT) in MATLAB. From the results, it was concluded that the spectral data is vital one for characterizing the drill bit. Futo et al. [39] discussed the possible use of drilling operational parameters and equivalent acoustic signal data for identifying the rock type. Patrik et al. [40] processed the vibro-acoustic signal gathered during rotary drilling of sedimentary and igneous rocks and tabulated the range of dominant frequencies of respective rocks and also discussed the possible use of dominant frequencies to obtain the dynamic properties of the drilling process. From the above discussions, it can thus be concluded that different techniques or approaches during drilling can be used to investigate the rock properties and identification of rock type.

The drilling process has been widely used in all engineering fields like mining, petroleum, civil, etc. The rock characterization during drilling is found to be easier and quicker [31-32]. In general, the drilling process causes vibration in drill bit or whole machine. The vibration induced in drill bit or in the whole machine is mainly due to use of different operational parameters of the drilling machine and the mechanical properties of the material to be drilled. The vibration parameters have a close relationship with .mechanical properties of the material to be drilled [41].

In this research, an attempt is made to predict the rock properties through the use of drilling operational parameters and equivalent most dominant frequency (MDF) extracted from vibration signal captured at spindle head during rotary type rock drilling. The prediction of rock properties using the dominant frequency of vibration can be very helpful as this frequency is independent of the vibration level or distance of measurement. In addition, the application of the dominant frequency of vibration can be very useful for estimation of rock properties directly at the drill site. The concept of using the dominant frequency of vibration for quantification of physico-mechanical properties is not yet reported in any literature to the knowledge of authors. It is anticipated that the dominant frequency of vibration produces at spindle head will vary during the drilling of different type of rocks for a particular drilling machine.

2. Experimental setup

The experimental setup consists of a medium size rotary type drilling machine with a loading arrangement, vibration measurement system and six types of sedimentary rocks having different compressive strength, tensile strength, and density.

2.1. Drilling machine

In this experiment, a rotary drilling machine with different operational parameters i.e., the four different diameter diamond core drill bits, three-bit speeds and locally made loading arrangements to apply three variable loads were used for drilling the rock specimen. The machine is actually mounted with a spring-loaded lever mechanism to control the feed rate of the drill bit, but for the purpose of applying the load, some modifications are done for the same lever. The load is applied stepwise on the drill bit using the loading arm which is attached at the end of the lever as shown in figure 1.

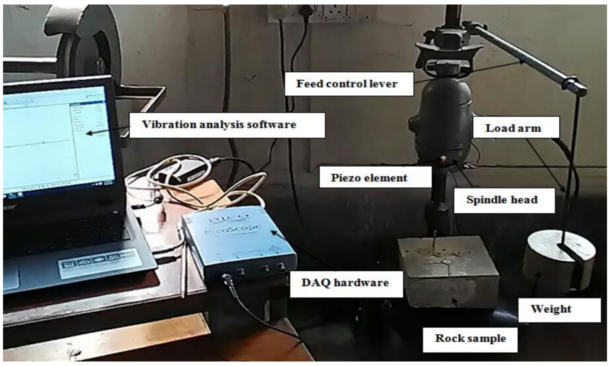


Fig. 1: Experimental Setup.

2.2. Rock samples used in the experiment

In this experiment, the sedimentary rock samples such as shale, chalk, siltstone, dolomite, sandstone and limestone were directly collected from the field. While collecting the rock samples, a proper inspection was carried out for macroscopic defects such as fractures and joints. The rock specimens were prepared by cutting off the rock samples into a cubic block of size 20 cm × 20 cm × 15 cm.

2.3. Vibration measurement

The vibration measurement system consists of a piezoelectric sensor, 4 channels data acquisition system and high-speed computer installed with vibration analysis application software.

2.3.1. Piezoelectric sensor

The Piezoelectric sensor, as shown in figure 2 is a sensing element widely used to sense the vibration of a system as it is highly sensitive, economic and easy to use. Piezoelectric sensors comprise a piezoelectric crystal which is mechanically coupled to an object that produces mechanical vibrations. The piezoelectric materials are capable of producing the voltage which is directly proportional to the vibration of the system. The sensors can be directly attached to the system where the vibration is to be found using the suitable adhesives.

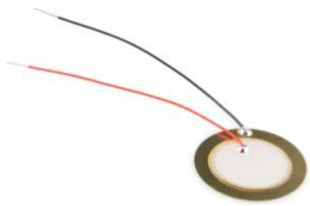


Fig. 2: Piezoelectric Sensor.

2.3.2. DAQ hardware

The DAQ hardware as shown in figure 3 is an ideal 4-channel data acquisition system for general purpose and high precision use. In general, the DAQ is a signal conditioning device which converts the analog vibration signal sensed by the piezoelectric sensor into a digital signal.

Fig. 3: DAQ Hardware.

2.3.3. Vibration analysis application software

The main function of vibration analysis application software is to process the digital signal received from the DAQ hardware and presents the vibration signal (time-domain) data to the end user. In this work, the picoscope 6.0 application software was used for capturing, analyzing and presenting the vibration signal data.

2.4. Arrangement of DAQ system for acquisition of the vibration signal

The data acquisition system (DAQ) is used to measure the physical property of a phenomenon.DAQ system is more accurate and also convenient as the data can be acquired and stored. In this experiment, the data acquisition system (DAQ) was used to acquire the vibration signal emanating from the spindle head. Figure 4 shows the schematic arrangement for measurement of the dominant frequency of vibration at spindle head.

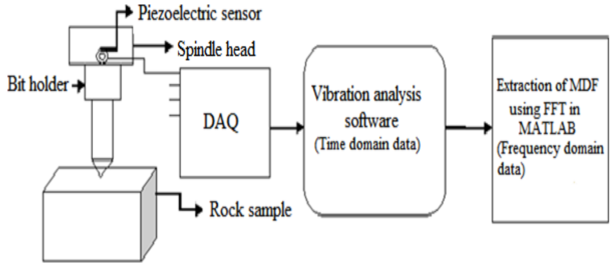


Fig. 4: Acquisition of Vibration Signal Using DAQ.

A piezoelectric sensor is attached to the spindle head using the suitable adhesives and is connected directly to the DAQ hardware through a single-ended BNC connector to any one of the DAQ channels. The DAQ hardware is connected to a high-speed computer installed with vibration analysis application software. During the drilling of rock for a particular drilling operational parameter, the time domain vibration signalemanating from the spindle head was captured using the vibration analysis application software. Later the frequency spectrum of the particular time-domain vibration signal is derived using the Fast Fourier Transformation (FFT) in MATLAB and thus the value of the most dominant frequency of vibration is collected. An example of the signal graph of vibration emanating from the spindle head during the drilling of shale under the particular operating condition is shown in figure 5.

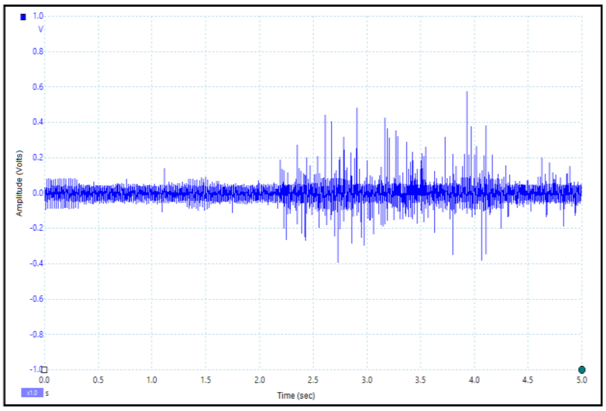
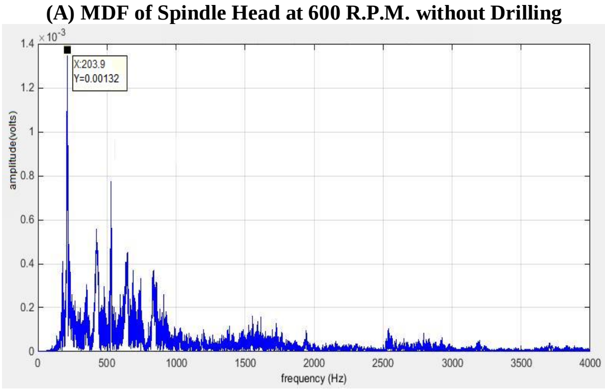


Fig. 5: Time Domain Vibration Signal.

2.5. Most dominant frequency (MDF)

The most dominant frequency of vibration usually meant the one that carries more vibration energy with respect to all the other frequencies in the considered frequency spectrum. In the frequency spectrum, the corresponding frequency where the amplitude of vibration is more is called maximum or dominant frequency of vibration. Most dominant frequency is widely used for assessment of fault detection process of mechanical machinery as the part of the condition monitoring maintenance program. In general, the dominant frequency is useful for analysis or charecterisation of a signal which is either electrical or mechanical type. In this experiment, the MDF values from the time domain vibration signal are extracted using the Fast Fourier Transformation (FFT) in MATLAB. The MATLAB is very fast and much convenient for extracting the frequency component from the acquired signal. Before drilling each rock type, the consistency of MDF of spindle head was checked when the machine is running at the maximum speed of 600 r.p.m without drilling. The MDF of spindle head was found approximately 204 Hz every time before actual drilling of each rock type as shown in figure 6 (a). Figure6 (b) is an example of MDF excited at spindle head during drilling of shale at particular operating conditions. In this, the frequency component of 524 Hz was extracted from the vibration signal.

(A) MDF of Spindle Head at 600 R.P.M. without Drilling



(B) MDF of Spindle Head during Drilling of Shale.

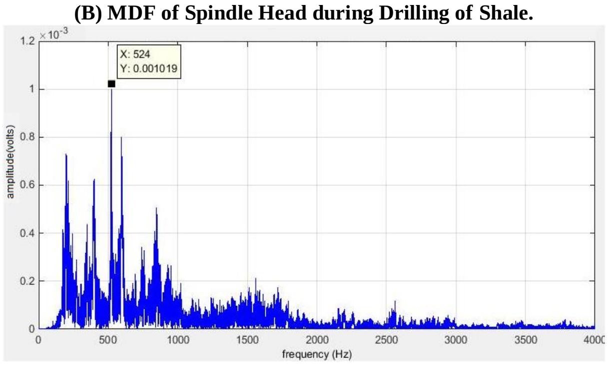


Fig. 6: Examples of the Dominant Frequency of Vibration.

3. Methodology

3.1. Determination of MDF at spindle head

The experimental setup for determination of the dominant frequency of vibration at spindle head during drilling of sedimentary rocks is shown in figure 1. The rock specimen is placed on the machine table beneath the rubber sheet in order to avoid the machine vibration transmitting from table to specimen. The machine operating or test conditions used for drilling each rock was the combinations of drill bit diameter of 12, 14,16 and18mm, the drill bit load of 5, 10 and 15 kgs, and the drill bit rotational speed of 400, 500 and 600 r.p.m. During the drilling, the particular size drill bit was advanced through the rock specimen due to particular drill bit load and rotational speed. The holes are drilled on each rock specimen using 36 set of test conditions. For each hole, the vibration signal emanating from the spindle head as shown in the figure 5 was captured through the vibration measurement system. During the drilling of each hole for a depth of 30mm, the vibration signal emanating from spindle head was captured five times and each time the capturing time was five seconds. The purpose behind capturing the signal five times during the drilling of 30mm hole depth is to check the consistency of MDF and it was found that the extracted MDF values from time domain vibration signals were almost consistent. However, the arithmetic average value of each set of five MDF was calculated to determine the equivalent MDF for a particular test condition. In this experiment, a total of 216 (i.e., 36 test conditions x 6 rock types) time-domain vibration signal was captured and the FFT in MATLAB was used for extracting the same number of MDF values from time domain vibration signals.

3.2. Determination of rock properties in laboratory

a. Determination of uniaxial compressive strength.

In many mining projects, the compressive strength of rock mass is most often determined. The UCS of all rocks was determined in rock mechanics laboratory using micro-controlled type AIM-317E-MU compression testing machine. This machine is mounted with an intelligent pace rate controller and having load bearing capacity of 2000 kN. An NX size specimen having a diameter of 54 mm and a length of 135 mm were prepared and the UCS of rock specimen was determined as per the guidelines suggested by ISRM. Before testing the specimen for UCS, the specimen was completely dried using an electric oven. At least three specimens were used for testing the UCS and arithmetic mean of all three rock specimen was considered for analysis purpose. The UCS of rock specimen was calculated as follows

$$UCS = \frac{F}{A} \text{ in MPa}$$

Where,

F = specimen failure load in Newton,

A = cross-sectional area of the specimen in mm^2

b. Determination of Brazilian tensile strength

Tensile strength is an important rock property as it is used for boreability predictions along with the uniaxial compressive strength of the rock and also useful in rock bolting operations. Usually, the rock materials exhibit low tensile strength because of the presence of microcracks in the rock materials. The Brazilian tensile strength machine with 100 KN loading frame capacity was used to determine the Brazilian tensile strength. NX-size core rock specimens having a diameter of 54 mm and thickness 27 mm were used as suggested by ISRM standards [42]. At least three specimens of the same type were used for testing the Brazilian tensile strength, and the arithmetic average of all the three specimen test values was considered.

The tensile strength of the specimen is calculated as follows:

$$\sigma_t = \frac{2 \times P}{\pi \times D \times t} \text{ in MPa}$$

Where

σ_t = Tensile strength in N/mm^2

P = Load at which the specimen failed

D = Specimen diameter in mm

t = Specimen thickness in mm

4. Results and discussion

The values of rock properties measured in the laboratory such as UCS, Brazilian tensile strength, density and the maximum and minimum values of most dominant frequency of vibration of each rock from the 216 data set of all rocks are summarized in table 1. The predictive models were developed through multiple regression analysis method using the Minitab 18 software.

Table 1: Physico-Mechanical Rock Properties and Range of Most Dominant Frequency Values Obtained at Spindle Head during Drilling of Sedimentary Rocks

Rock sample	UCS (Mpa)	BTS (Mpa)	Density (kg/m^3)	MDF (Hz)	
				Min	Max
Shale	16.3	1.98	2065	321	708
Chalk	23.1	2.83	2239	353	798
Siltstone	58.6	4.91	2498	439	963
Dolomite	66.9	5.49	2612	465	1020
Sandstone	87.2	7.20	2649	580	1275
Limestone	121.6	9.60	2730	841	1848

(*MDF=Most Dominant Frequency)

4.1. Analysis of data using multiple regression method

In general, the multiple regression method is widely used to establish the relationship between independent variables or predictors and a dependent variable. In this study, a total of 216 test condition data were used to develop the second-order multiple regression model. The mathematical modeling of the most dominant frequency of vibration at spindle head during drilling is affected by many factors which directly and indirectly act in a very complex manner. Therefore for representing the detailed process, a second-order model is preferred. The ANOVA was conducted to obtain the detailed information about by how much each independent variable is influencing the dependent variable. In the present study, four vital factors or independent variables were considered. They are weight on bit in kg (W), the rotational speed of drill bit in r.p.m. (S), drill bit diameter in mm (D), and equivalent most dominant frequency of vibration in Hertz (Z). The considered responses are a uniaxial compressive strength, Brazilian tensile strength, and density. The mathematical model for establishing the relationship between rock properties and considered independent variables can be written as $y = f(x_1, x_2, x_3) + \psi$ where y is the dependent variable and x_1, x_2 and x_3 are the independent variables and ψ is a fitting error. The function 'f' for the second order model can be written as:

$$f = a_o + \sum_{i=1}^{n} a_i\, x_i + \sum_{i=1}^{n} a_{ij} x_i^2 + \sum_{i<j}^{n} a_{ij}\, x_i x_j + \psi \tag{1}$$

Where a_i represents the linear effect of x_i, a_{ij} represents the quadratic effect of x_i, and a_{ij} in the fourth term represents the linear interaction between x_i and x_j.

To develop the multiple regression models, the backward elimination method was used. In ANOVA table, if absolute t value of the particular independent variable was not greater than the tabulated t value at 95% confidence level, then the considered independent variable was removed and the multiple regression procedure was continued until the t values of remaining independent variables get statistically significant and the corresponding generated regression model was selected.

4.1.1. Prediction model for uniaxial compressive strength

The best mathematical model developed for UCS is:

$$UCS = 95.5 - 8.06 \times W - 0.663 \times S + 3.903 \times D + 0.2495 \times Z + 0.1720 \times W^2 + 0.000506 \times S^2 - 0.000098 \times Z^2 + 0.001747 \times W \times Z + 0.000078 \times S \times Z \tag{2}$$

Table 2: A Model Summary for the Dependent Variable (UCS)

R^2	Predicted R^2	Adjusted R^2	Estimated error
0.9178	0.9084	0.9142	10.6030

From table 2(a) it was concluded that all the terms generated in multiple regression are able to explain the variance up to 91.78% in response (UCS). The regression coefficients and their significance are illustrated intable 2(b) for estimation of UCS. In this, the values of p for all the terms in developed model are statistically significant as the $p < 0.05$ for 95% confidence level and also the computed absolute t values are greater than the tabulated t values (for 95% confidence level and 9 degrees of freedom, for $k = n – 1$, $t = 1.860$). Itis therefore concluded that all the terms generated in the regression model are significantly influencing the UCS. The ANOVA table 2(c) illustrates the degrees of freedom (DF), mean squares (MS), F value and p-value of the generated regression model for UCS. Figure 7 shows the comparison of UCS measured in the laboratory and the UCS predicted from the developed model.

Table 2:B Regression Coefficients for UCS

Variables	Coefficients	t-value	p-value
Constant	95.5	2.44	0.000
W	-8.06	-6.30	0.000
S	-0.663	-4.29	0.000
D	3.903	11.73	0.000
Z	0.2495	14.36	0.000
W^2	0.1720	2.72	0.007
S^2	0.000506	3.25	0.001
Z^2	-0.000098	-13.14	0.000
W×Z	0.001747	2.44	0.015
S×Z	0.000078	2.39	0.018

Table 2:C ANOVA for UCS

Source	Degree of free-dom	Mean square	Sum of squares	F-value	p-value
Regression	9	28716	258504	255.49	0.000
Error	206	112.4	23159		
total	215				

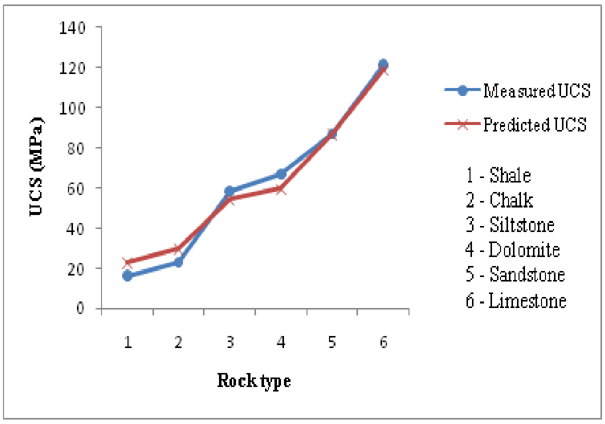


Fig. 7: Comparison of Measured and Predicted UCS.

4.1.2. Prediction model for Brazilian tensile strength

The best mathematical model developed for BTS is:

$$BTS = 7.65 - 0.5636\times W - 0.0470\times S + 0.2784\times D + 0.01762\times Z + 0.01245\times W^2 + 0.000036\times S^2 - 0.000007\times Z^2 + 0.000106\times W\times Z + 0.000005\times S\times Z \quad (3)$$

From table 3(a) it can be observed that all the terms generated in multiple regressions are able to explain the variance up to 92.52 % in response (BTS).

Table 3:A Model Summary for the Dependent Variable (BTS)

R^2	Predicted R^2	Adjusted R^2	Estimated standard error
0.9252	0.9162	0.9219	0.7178

The regression coefficients and their significance are illustrated in table 3(b) for the estimation of BTS. The values of p for all the terms in developed model are statistically significant as the $p < 0.05$ for 95% confidence level and also the computed absolute t values are greater than the tabulated t values (for 95% confidence level and 9 degrees of freedom, for $k = n – 1$, $t = 1.860$), so that it is concluded that all the terms generated in the regression model are significantly influencing the BTS. The ANOVA table 3(c) illustrates the degrees of freedom (DF), mean squares (MS), F value and p-value of regression model for BTS.

Table 3:B Regression Coefficients for BTS

Variables	Coefficients	t-value	p-value
Constant	7.65	2.89	0.000
W	-0.5636	-6.50	0.000
S	-0.0470	-4.50	0.000
D	0.2784	12.35	0.000
Z	0.01762	14.97	0.000
W^2	0.01245	2.91	0.004
S^2	0.000036	3.44	0.001
Z^2	-0.000007	-13.21	0.000
W×Z	0.000106	2.18	0.030
S×Z	0.000005	2.33	0.021

Table 3:C ANOVA for BTS

Source	Degree of free-dom	Mean square	Sum of squares	F-value	p-value
Regression	9	145.85	1312.7	283.07	0.000
Error	206	0.515	106.14		
total	215				

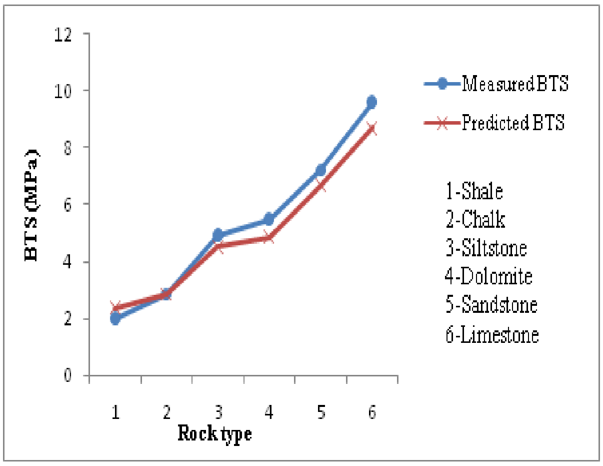


Fig.8: Comparison of Measured and Predicted BTS.

Fig. 8 shows the comparison of measured BTS and the BTS predicted from the developed model.

4.1.3. Prediction model for density

The best mathematical model developed for density was:

$$Density = 1476 - 51.28\times W - 1.761\times S + 61.8\times D + 2.520\times Z - 0.001201\times Z^2 + 0.04088\times W\times Z + 0.001509\times S\times Z - 0.0510\times D\times Z \quad (4)$$

From table 4(a) it was concluded that all the terms generated in multiple regression are able to explain the variance up to 79.82 % in response (Density).

Table 4:A Model Summary for Dependent Variable (Density)

R^2	Predicted R^2	Adjusted R^2	Estimated standard error
0.7982	0.0.7798	0.7904	108.895

The regression coefficients and their significance are illustrated in table 4(b) for estimation of density. The values of p for all the terms in developed model are statistically significant as the $p < 0.05$ for 95% confidence level and also the computed absolute t values are greater than the tabulated t values (for 95% confidence level and 8 degrees of freedom, for $k = n – 1$, $t = 1.895$), so that it is concluded that all the terms generated in the regression model are significantly influencing the density. The ANOVA table 4(c) illustrates the degrees of freedom (DF), mean squares (MS), F value and p-value of the generated regression model for BTS. In addition, the computed F values for all three models are greater than the tabulated F values, so that it indicates the adequacy of the developed models to explain the response. Figure 9 shows the comparison of measured density and the density predicted from the developed model.

Table 4:B Regression Coefficients for Density

Variables	Coefficients	t-value	p-value
Constant	1476	7.16	0.000
W	-51.28	-8.70	0.000
S	-1.761	--6.40	0.000
D	61.8	6.02	0.000
Z	2.520	8.89	0.000
Z^2	-0.001201	-14.01	0.000
W×Z	0.04088	5.65	0.000
S×Z	0.001509	4.49	0.000
D×Z	0.0510	-4.05	0.000

Table 4:C ANOVA for Density

Source	Degree of freedom	Mean square	Sum of squares	F-value	p-value
Regression	8	1213510	9708079	102	0.00
Error	207	11858	2454647		
total	215				

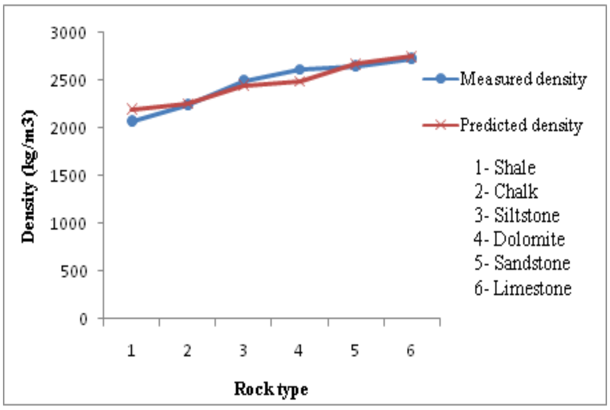


Fig. 9: Comparison of Measured and Predicted Density.

5. Evaluation of prediction performance of the developed models

In the present study, the prediction performances of the developed models are investigated using the three indices known as variance account for (VAF), root mean square error (RMSE) and mean absolute percentage error (MAPE) [3, 32, 43–45].

$$VAF = \left[1 - \frac{Var(y - y')}{Var(y)} \right] \times 100 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y - y')^2} \tag{6}$$

Where y and y' are the measured and predicted values of the response respectively. The model would predict the response with 100% perfection with zero errors if VAF and RMSE values are 100 and 0 respectively. The MAPE indicates the absolute percentage error or accuracy in terms of percentage of the developed prediction model and is calculated by the equation:

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(M_i - P_i)}{M_i} \right| \times 100 \tag{7}$$

Where M_i is the measured value and P_i is the predicted value. The values of VAF, RMSE, and MAPE for the developed models are tabulated in table 5.

Table 5: Indicators of Prediction Performance of the Developed Model

Dependent variable	Indices of performance		
	VAF (%)	RMSE	MAPE (%)
UCS(Mpa)	91.75	10.37	20.64
BTS(Mpa)	91.60	0.82	13.76
Density (gm/cc)	79.81	0.106	3.54

Table 6: Strength of Correlation of Measured and Predicted Response

Dependent variable	Pearson correlation coefficient (r)
UCS	0.96
BTS	0.96
Density	0.83

In addition, the strength of the relationship between measured and predicted value of UCS, BTS, and density is checked using the Pearson correlation coefficient and is found very strong for all dependent variables or responses as shown in table 6.

6. Conclusion

The prediction of UCS, BTS, and density were carried out using the most dominant frequency of vibration induced at spindle head considering the effects of drilling operational parameters during rotary drilling. For each rock property, the predictive models were developed using second-order multiple regression analysis. The evaluation of prediction performance of the developed model indicates that the predictive models can be reasonably used for estimation of physico-mechanical properties such as UCS, BTS and density of rocks during the preliminary stage of mining design projects as this approach is easy, less time consuming and also economical. The proposed method has more advantage over the other methods as the number of rock properties can be estimated directly at drill site with a single experiment. In the future, it is suggested to use other drilling operational parameters to investigate the reliability of this method.

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