

Indirect estimation of compressive and shear strength from simple index tests

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Abstract Uniaxial compressive and shear strength are two of the very important parameters, commonly required in the initial stages of planning and design of rock engineering projects. So, an attempt has been made in this study to predict compressive and shear strength (output) of rocks from some simple and easily determinable parameters in laboratory viz., point load index, tensile strength, unit weight and ultrasonic velocity (input). Failure modes have also been studied and correlated with their ultrasonic velocity. The study uses two of the most commonly used predictive mathematical techniques: statistical analysis and neural networks to predict the strength parameters. The regression analysis shows that the rock quality parameters are very well correlated with the ultrasonic velocity except for the unit weight. Unlike few researchers in the past, a linear correlation was best suited for the rock quality parameters in this study. On the other hand, Artificial Neural Network (ANN) was able to predict the same strength parameters with a better reliability than regression analysis. The study shows that the proposed method for the prediction of UCS and shear strength is acceptable and can be reliably applied in various rock engineering problems.

Keywords Compressive strength · Shear strength · Regression analysis · Artificial neural network · P-wave velocity

1 Introduction

Failure mechanisms in rock have been studied since 1960s and still continue to be a fascinating topic. Owing to the complexity observed in rock masses due to discontinuities, textural distribution and grain size, strength varies drastically. Various failure modes have been observed when these complex materials are used as a construction material. The most commonly observed failures result either solely from compression, tension and shear mode or a combination of any of them due to load imposed by the engineering structures [8]. Determination of mode of failure provides useful information for the economic and safe design of engineering structures [43].

Most of the construction materials have to undergo rigorous testing following certain standards, before being used in any design purpose. The need to cater to the specification of the standards often makes it very difficult for the engineers to obtain the strength parameters in the initial stages of construction. Moreover, these tests are very costly and require great precaution and mechanical precision while testing, not to mention the time involved from preparation of samples to testing [9, 19]. Often, lack of availability of high end instruments and inability to prepare standard samples or even unavailability of samples itself can delay the construction activities. Therefore, an alternate and equally significant method has to be used in such cases to determine the strength parameters effectively. Previously, several researchers have opined the use of various simple and indirect tests like point load tests, sound velocity, density, impact strength, hardness, slake durability, rebound number and others to determine commonly used strength parameters which are difficult to determine through standard tests [29, 39, 56].

P-wave velocity is known to show very good correlation with a number of intact rock properties such as compressive strength, tensile strength, point load index, elastic modulus,

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density as well as porosity [12, 29, 33, 40, 55, 56, 66]. Subsequently, a number of researchers have investigated the effect of different parameters such as specimen length, rock fabric, joint roughness, saturation, pH of water, weathering, distribution of micro-cracks, temperature, porosity and clay content on P-wave velocity [5–7, 21, 23, 30, 35, 49, 50, 63]. The advent of new technology in the field of rock physics has made the onsite measurement of P-wave velocity very easy. Therefore, P-wave can be considered as a reliable parameter for the estimation of strength parameters of intact rocks. Point load index of rocks can be determined on any shape of sample which saves us from the toil of preparing standard complying samples unlike UCS. Similarly, determination of tensile strength involves small disc shaped samples which is easier as compared to UCS, and unit weight employs the Archimedes principle for its determination which is also fairly easy. Considering the ease of determination of these parameters (P-wave velocity, Tensile strength, Point load index and Unit weight) over others, these are used as the predictors in this study. These four easy to determine and simple parameters were considered as input parameters to indirectly calculate the compressive and shear strength of the rocks. Moreover, these are well-established parameters and well correlated with other rock strength parameters. Mishra and Basu [44] performed a series of tests on granite, schist and sandstone to obtain several parameters like PLI, Schmidt rebound hardness, density, V_p and block punch index and were able to obtain very good correlation with each other.

The increasing use of statistical methods and artificial neural network (ANN) in rock mechanics to correlate and estimate various parameters in a fast, reliable and economical way has made them extremely popular among rock engineers. Huang and Wanstedt [25] suggest that a neural network is a good approach for complex mechanisms such as those encountered in rock engineering problems, in which many factors have their influence on the process as well as the result. Most of the rock parameters cannot be determined in the field, thus posing an immediate need for their reliable prediction from easily determinable parameters. In such conditions, indirect methods like ANN and statistical methods come handy which are also considered as very reliable and accurate tools for prediction of rock quality parameters [11, 36, 45, 47, 54].

2 Methodology

2.1 Sample preparation

Several rock cores were collected from different parts of India, representing a total of eight different rock types, namely quartz mica schist, weathered basalt, limestone,

Table 1 Procedure used for sample preparation and estimation of test results

Parameters	Procedure
UCS	ASTM D7012 [3]
Tensile strength	ASTM D3967 [1]
Shear strength	Protodyaknov [52]
Point load Index	ASTM D5731 [2]
Unit weight	ASTM D7263 [4]

gneiss, quartzite, dolomite, shale and sandstone. The rocks belong to different formations and have been collected from surficial level, not more than 20 m depth. Core specimens of equal diameter (NX size) and length ($2.5 \times D$) were prepared for all the rock types, corresponding to each test following ASTM standards (Table 1). To remove the effect of natural moisture in rocks, all the rock samples were oven dried at $105^\circ \pm 2$ for 24 h. Samples were prepared for the laboratory determination of intact properties of uniaxial compressive strength (UCS), tensile strength (TS), shear strength (SS), point load index (PLI) and density (D) for all the rock types following appropriate standards (Table 1). Shear strength was determined from the methodology adopted by Protodyaknov [52], using cylindrical samples.

2.2 Failure modes

Several samples of eight different rock types were tested under uniaxial compression mode to observe their failure patterns. Basu et al. [8] have studied failure behavior for three different rock types under varying failure modes and grouped them under six different categories (axial splitting, shearing along a single plane, double shear, multiple fracturing, along foliation, and Y-shaped). In this study, axial splitting is mostly observed for different rock types; however, multiple fracturing and shearing along a single plane are also observed in a few samples like shale and quartz mica schist (Fig. 1). Higher strength rocks like gneiss and quartzite show multiple fracturing as has also been reported in Basu et al. [8]. In the absence of any predefined weak planes in limestones and weathered basalts, axial splitting is very common. Failure in quartz mica schist and gneiss develops as a function of local foliation planes and fails partly along them and partly in other modes. Most of the samples obtained are tested in such a manner that they are free of any predefined weak planes to reduce the heterogeneity. According to Wong et al. [64], failure by axial splitting is very common in cylindrical specimens which has also been reported by other researchers for different rock types like marble [51] and quartzite [18]. Jaeger and Cook [27] suggest that shear and wedge-shaped fragments under uniaxial compression are a result of end effects of

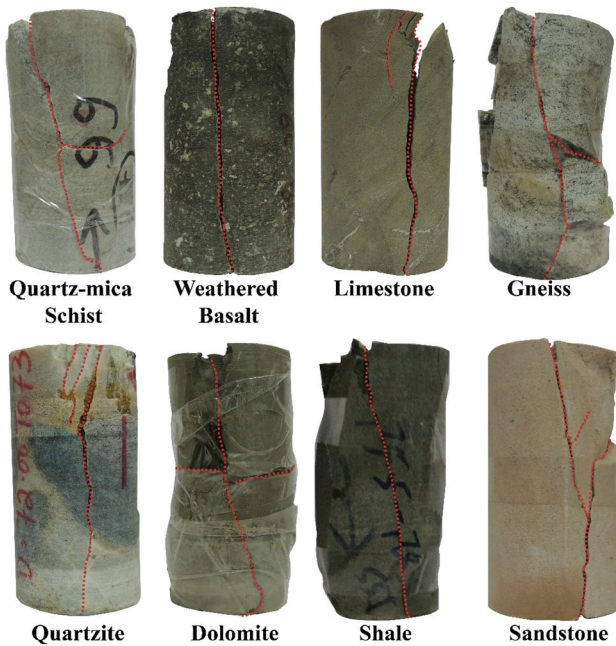


Fig. 1 Common failure modes observed in different rock types

specimen. Holzhausen and Johnson [24] have analyzed a series of mechanism responsible for axial splitting under uniaxially loaded cylindrical specimens. Buckling of rocks away from internal surface and interaction of open

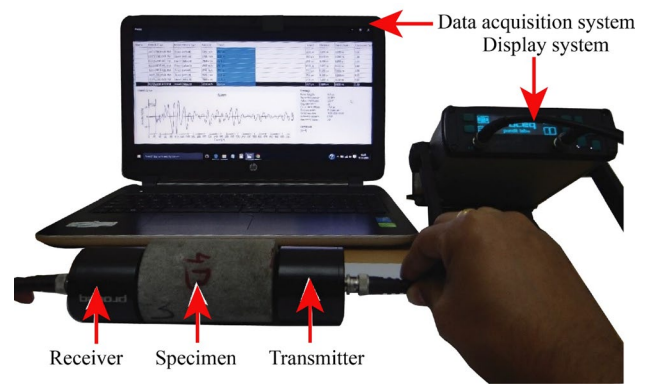


Fig. 2 Set up for ultrasonic wave velocity measurement

fractures with free surface of the specimen are two of the common causes for axial splitting in rocks.

2.3 Ultrasonic velocity measurement

It is a non-destructive technique often used to study dynamic properties of rocks. Since this test is easy to perform in the field and gives good result in less time, it has become one of the most useful tests in geotechnical engineering. The ultrasonic velocity traveling through solids depends on the density and elastic characteristics of the material. A coupling gel was used to avoid the presence of air gaps between contact surface of rock and

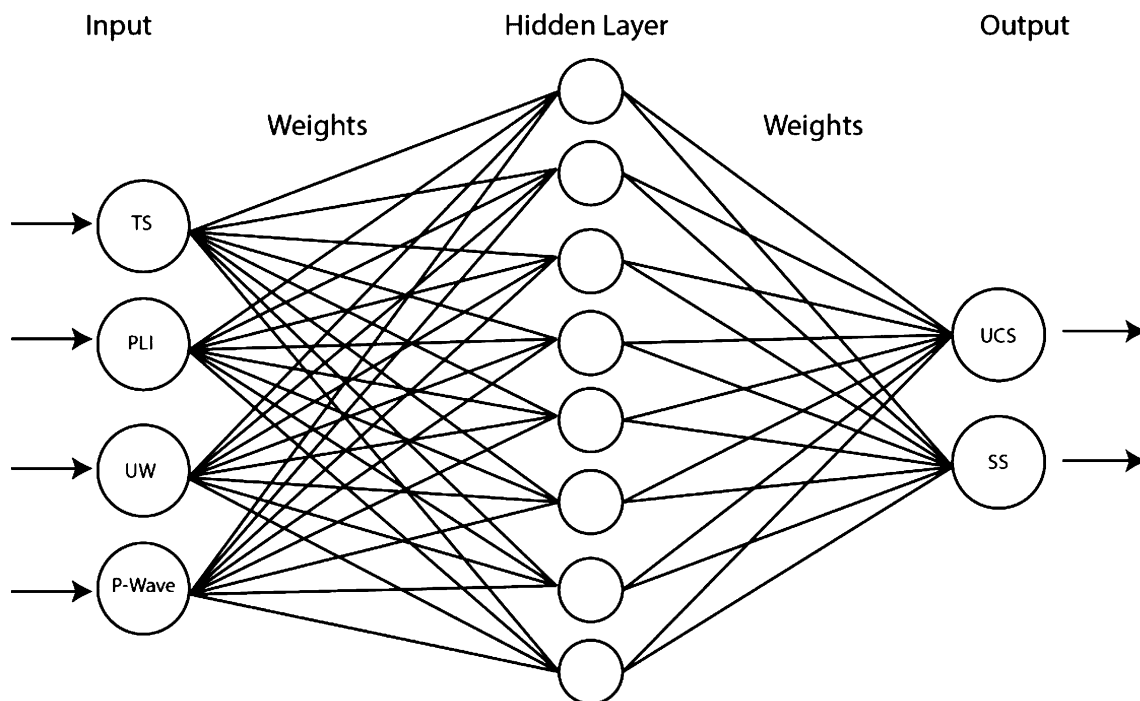


Fig. 3 A three-layered ANN structure implemented in this study

transducers. The factors which influence seismic velocities in solids vary with lithology, density, shape, size, porosity, anisotropy as well as the presence of discontinuities like joints, fractures and bedding planes [31]. Sub-axial splitting observed in most rocks suggests that the cylindrical specimens were free of any directional anisotropies. This helps in obtaining better control and reliable values of ultrasonic velocity to be used as an input parameter. The P-wave velocities were determined by Portable Ultrasonic Non-destructive Digital Indicating Tester (PUNDIT) on a cylindrical sample of NX (54 mm) size diameter (Fig. 2).

2.4 Regression analysis

Regression analysis is a statistical tool for estimating relationship between variables and predicting unknown from known parameters [60, 65]. Depending on the complexity and number of data sets, simple or multiple regression analysis is chosen. A scatterplot is prepared for entire dataset which is very helpful in knowing the trend of the variables. Subsequently, curve fitting is done which provides two important data. The first is the equation of the curve for which linear regression is in the form of $Y = mX + C$, where Y is dependent and X is independent variable and m is the slope of the curve. The other valuable number is correlation coefficient which measures the degree of association of the two variables.

2.5 Frequency distribution

The distribution of data sets can be properly represented through frequency distribution plots. This statistical technique allows users to quantify the data in a more organized manner. Normal distribution was used for curve fitting as it is the most important and commonly used distribution function in geotechnical engineering. It has been observed that most natural phenomenon involving many accumulating factors tends to show normal distribution [20]. A random variable X follows a normal distribution if its probability density function has the form

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad \text{where, } -\infty < x < \infty$$

2.6 Artificial neural network

ANN is a very intelligent soft computing tool that has been used to predict various complex parameters in the recent past. It is a neuron-based system that uses its

previous learnings from a set of data to assign a reasonable value to the output parameters for a similar kind of new data set. The structure and data processing technique of ANN is inspired by the human brain. The configuration of ANN is composed of a highly layered structure that constitutes many simple processing elements (called neurons) capable of performing highly complex computations for data processing and knowledge representation [38]. The layered structures of the neurons are connected to each other and each connection is called as weight [42, 62]. Many researchers have discussed the working and principles of ANN earlier and can be referred [37, 41, 46, 54].

In the current study, feed-forward back propagation network is used which is a multi-layered perception network. The back propagation algorithm is selected over other algorithm because of its versatility and ease of use. A back propagation neural network has at least three-layered structure which contains, an input layer, one or more hidden layers and an output layer. Such kind of network compares the predicted output value with the assigned target value and estimates the error associated with it. With each iteration, it reduces the associated error and produces a more accurate prediction. De Villiers and Barnard [15] concluded that there is no significant difference in the performance of three- and four-layered nets and that the three layered nets are capable of better classification. Therefore, the network structure employed in the present study consists of three layers. Depending on the complexity of the problem, the number of neurons in the hidden layer can be varied. The hidden layer was assigned a logarithmic sigmoid transfer function with eight neurons, chosen on the basis of minimum root mean square error and the output layer was assigned tangent sigmoid transfer function. Gradient Descent (TRAINGD) is employed as the training function. An adaptive learning function LEARNGDM is used for the learning task. Tensile strength, point load index, unit weight and P-wave velocity are taken as the inputs and accordingly four input neurons are considered. UCS and shear strength are taken as two output parameters and two neurons are assigned to them in the output layer. The network structure employed is shown in Fig. 3.

The data set is subjected to normalization to get good convergence of data. The normalization function used is shown in Rafiq et al. [53].

$$X_{\text{norm}} = \frac{X_{\text{actual}} - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}}$$

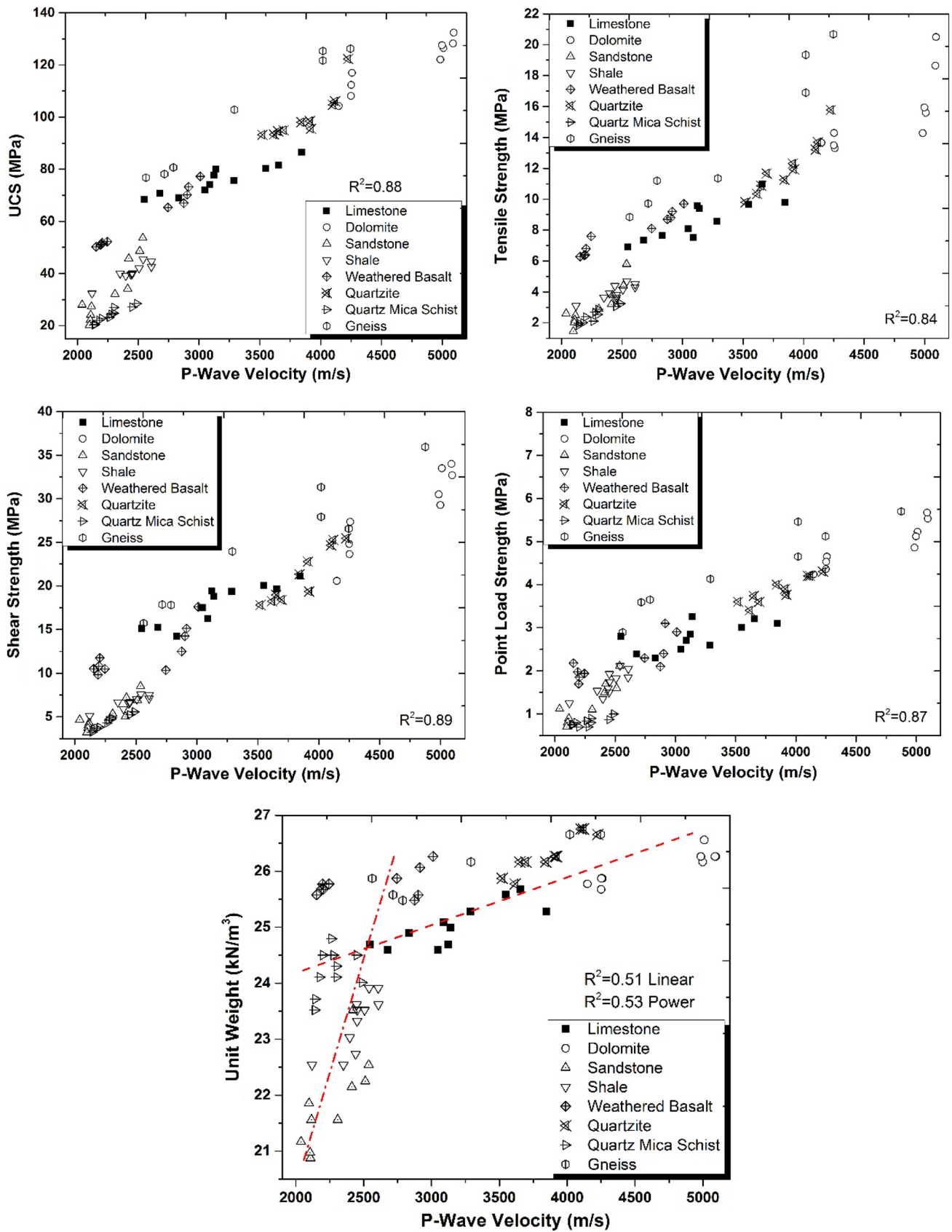


Fig. 4 Scatter plot of rock quality parameters with their respective sonic velocities

Table 2 Regression equations obtained from linear curve fitting on the scatter plot

Equation	Correlation coefficient (R^2)	RMSE
$UCS = 0.0372x - 45.499$	0.88	10.81
$TS = 0.0054x - 8.3622$	0.84	2.03
$SS = 0.0097x - 15.099$	0.89	2.98
$PLI = 0.0015x - 2.0449$	0.87	0.51
$UW = 6.0858x^{0.1755}$	0.53	

where X_{norm} is the normalized value, X_{actual} is the actual value, X_{max} is the maximum value of X in the data set and X_{min} is the minimum value of X in the data set.

3 Results and discussion

In this study, simple regression analysis was done to correlate some intact rock parameters with their respective ultrasonic velocity. Data from eight different rock types were plotted for UCS, tensile strength, shear strength, point load index and unit weight to develop a set of empirical equations with V_p . The rock quality parameters except unit weight show reliable correlation with V_p indicated by high correlation coefficients. The range of ultrasonic velocity encountered in this study varies from 2000 to 5000 m/s. Gupta and Seshagiri [22] conducted a series of tests on three crystalline rocks, viz. granite, basalt and quartzite and observed about 98 % reduction in strength (both UCS and PLI) and 97 % reduction in ultrasonic velocity due to weathering. In this study, four rock types of sedimentary origin were used which are only slightly weathered. Rocks like shale and few limestone samples showed very low strength possibly due to complex diagenetic history and porosity. In addition to diagenetic history and porosity, another important factor responsible for significant change in the sonic velocity in sedimentary rocks is clay content [13, 23, 61]. Previously, a number of researchers have correlated rock strength parameters with V_p and suggested linear [28, 44, 55, 56, 66] as well as non-linear correlation [17, 29, 34, 39, 48] for different rock types. Inoue and Ohomi [26] observed a poor correlation of velocity against density and UCS for poor strength rocks. However, a linear correlation showed relatively high reliability in this study, notwithstanding the fact that the data were more scattered towards higher strength rock. Although other curve fitting methods were also checked for the data sets, the best correlation was obtained in the case of linear curve fit (Fig. 4). Dolomite along with few samples

of quartzite and basalt shows high strength together with high V_p in this study. Individually, rock strength parameters vs V_p of dolomitic rocks do not display linear relationship, probably because of the post-metamorphic alteration. The presence of micro-cracks also has a large bearing in velocity reduction in hard rocks, especially at shallow depth where crack initiation and propagation are not influenced much by low confinement. Contrary to this, Nur and Simmons [50] conducted a series of experiments on the effect of saturation and pressure on low porous rocks and observed a strong dependency of V_p on saturation as well as pressure until very low confining pressures of less than 2 kbar. Weathering and alteration, bedding planes, texture, density, anisotropy, grain size and shape are identified as important parameters known to significantly affect porosity in non-sedimentary rocks [31]. Except, weathered basalt, all non-sedimentary rocks have relatively high strength and are also very dense. Clearly, two trends can be seen in density vs V_p , both linear, but the overall trend deviates from linearity (Fig. 4). The regression equation obtained by linear curve fitting for different rock quality parameters is shown in Table 2, except for unit weight which is non-linear.

The frequency distribution of UCS and point load index data shows symmetrical nature, which means a range of equally well-distributed data is found for these parameters (Fig. 5). A near normal distribution was also obtained by Yilmaz [68] with data slightly skewed towards left for several rock types, while Yesiloglu-Gultekin et al. [67] also showed normal distribution for UCS with a standard deviation of 25 and a mean of 114 MPa for granitic rocks. A number of researchers have correlated compressive strength and point load index of rocks and noted a linear relationship with high correlation coefficient [57, 59]. Bieniawski [10] suggested a factor of 24 for the conversion of index to strength values for tests conducted on NX size samples. However, Chau and Wong [14] suggested that index to strength conversion factor depends on compressive to tensile strength ratio, Poisson's ratio, length and diameter of the specimen and the factor 24 is not universal. The shear strength, tensile strength and unit weight are skewed either towards left or right. Both shear and tensile strength have a tendency to show lower values irrespective of higher values observed in compression. This also correlates well with the fact that rocks have the tendency to fail in tension or shear more easily than compression as a result of which tensile and shear strength values are on lower side. Most rocks generally show high density, unless weathered, which results

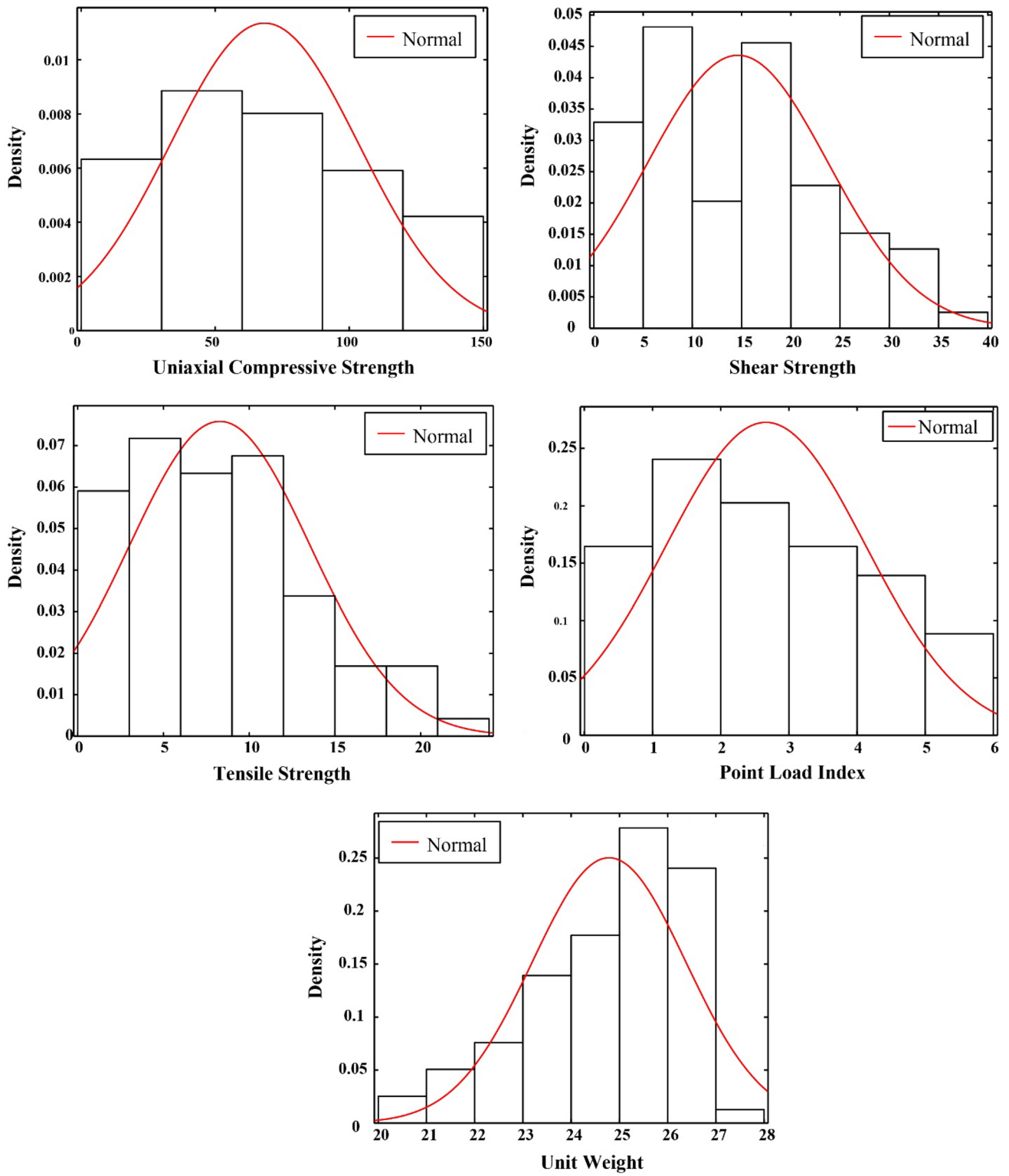


Fig. 5 Frequency distribution plot for the rock quality parameters

Table 3 Statistical data for the analyzed data for all the rock quality parameters

Strength parameters	Mean	Median	Standard deviation
UCS (MPa)	67.93	68.43	35.33
Tensile strength (MPa)	8.29	7.67	5.26
Shear strength (MPa)	14.62	14.25	9.15
P-wave velocity (m/s)	3061.70	2716.00	887.04
Unit weight (kN/m ³)	24.79	25.28	1.59

in high observed values of unit weight mostly in the range of 24–27 kN/m³. The statistical values like mean, median and standard deviation of all the parameters are also shown in the Table 3. A large standard deviation also indicates a range in the values observed for all the parameters.

For ANN, a total of 79 data were used for the analysis out of which 60 data were taken for training and validation and rest of the data were used to check the accuracy of the model. The validation plot shows a gradual fall in mean square error with increasing epoch (Fig. 6). The best performance is observed at 998 epoch and the validation line remains close to the best representing line. Regression plots for training, testing and validation are shown in Fig. 7. All the graphs show a high correlation coefficient exhibiting a better predictability of the desired output in this study.

The predicted data from ANN were plotted against the measured data sets for both the output parameters (Fig. 8). It is interesting to note that the results predicted through ANN is superior to the linear regression analysis. This has also been reported by a number of researchers in the past [16, 32, 57, 58]. Sarkar et al. [54] conducted a similar study with four different rock types to predict UCS and shear strength through ANN by taking point load index, V_p , slake durability index and density

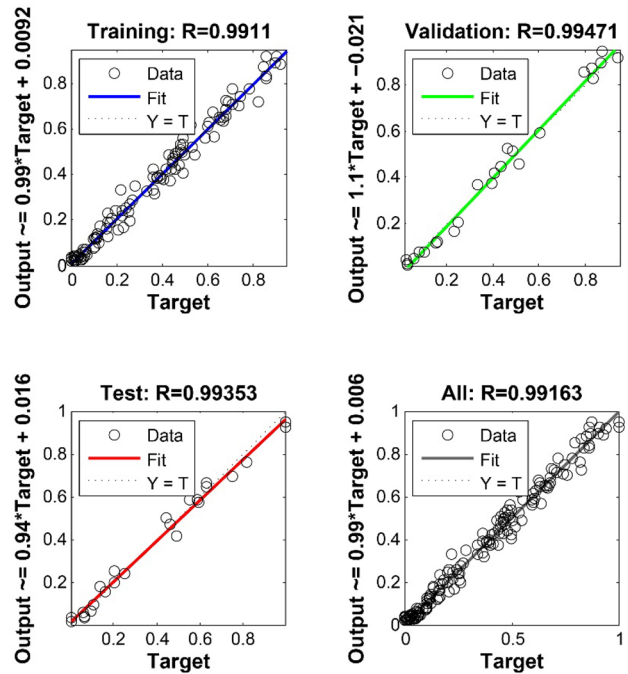
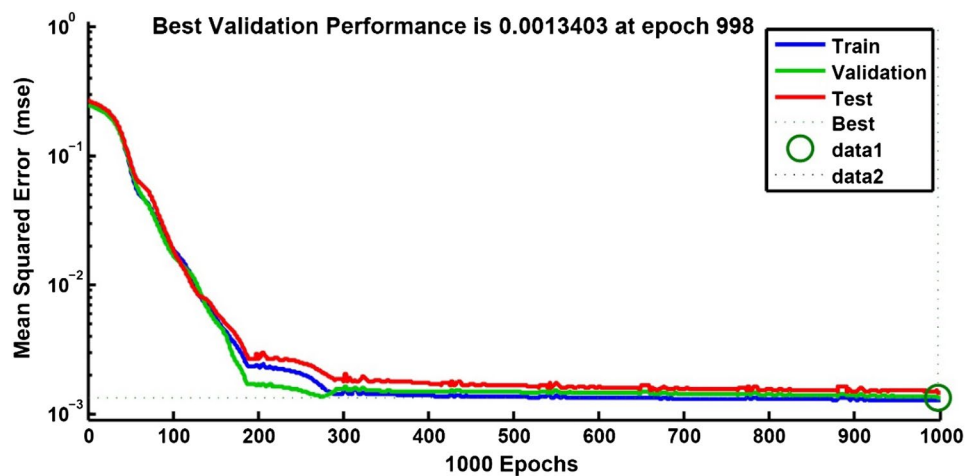


Fig. 7 Plots showing the degree of unity among target and output

as inputs. The results were very promising, showing high value of correlation coefficient and very less percentage error. Similarly, in this study, correlation coefficient of 0.98 and 0.97 for both UCS and shear strength, respectively, also shows a better reliability of these strength parameters in comparison to statistical analysis. The root mean square error (RMSE) for UCS and shear strength is 4.16 and 1.52, respectively, which is very insignificant and is in agreement with previous studies. A better prediction from ANN gives the confidence that the results from this analysis can be applied in different rock engineering problems.

Fig. 6 Performance plot of the neural network



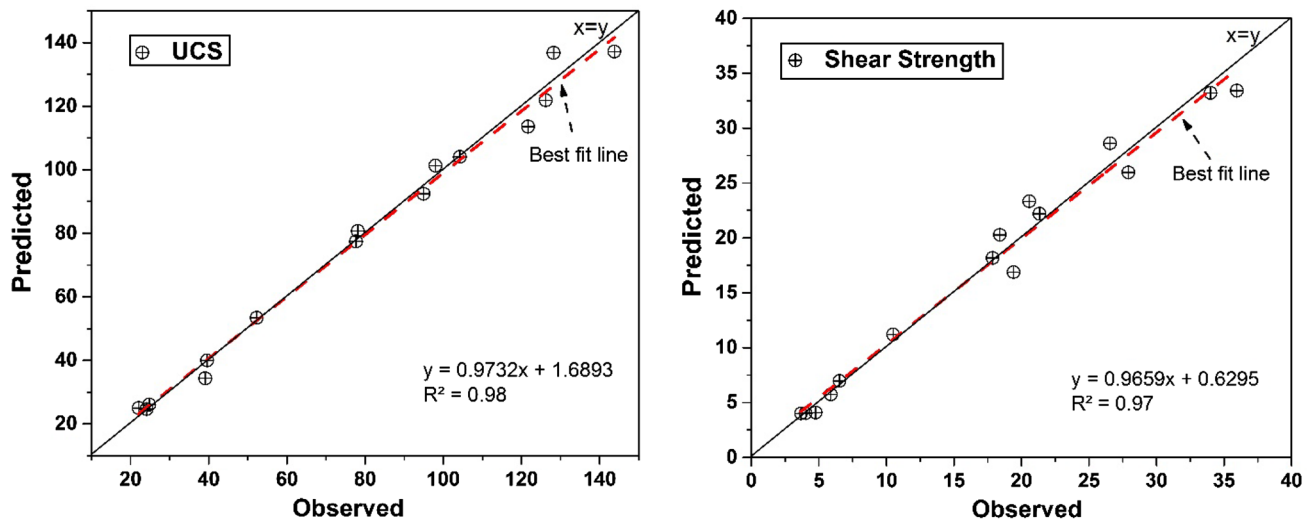


Fig. 8 Observed vs. predicted values of compressive and shear strength obtained from ANN

4 Conclusion

In this study, two of the most commonly used rock strength parameters, viz. UCS and shear strength were determined from simple index tests like PLI, unit weight, tensile strength and V_p . Regression analysis was used to correlate the rock quality parameters with their sonic velocities and subsequently develop empirical relations. This was followed by application of ANN to predict UCS and shear strength by taking other index parameters as input. The following results were obtained:

- A series of failure mode is observed under uniaxial compression, axial splitting being the most common. Failure along single shear plane and multiple fracturing is also observed in various specimens of different rock types.
- A linear correlation is obtained between rock quality parameters with V_p , except unit weight. The data points are more scattered towards the higher strength values suggesting poor relationship with sonic velocity. Linear correlation seems reasonable because of the absence of any weak planes like foliation/bedding planes, etc. along the loading direction.
- Two different trends are observed in unit weight vs V_p , both linear, but the overall trend is clearly non-linear.
- Overall, high correlation coefficients of 0.88, 0.84, 0.89 and 0.87 for UCS, tensile strength, shear strength and PLI, respectively, show good reliability for regression analysis.
- Frequency distribution plot for all the data sets properly fits with normal distribution function with slight skewness. A large standard deviation is observed for almost

all the parameters suggesting a wide range of strength data.

- The prediction capability of ANN is better than regression analysis, also in accordance with previous researchers. The relatively high correlation coefficient of 0.98 and 0.97 for UCS and shear strength, respectively, shows the effectiveness of ANN over simple regression analysis.
- Overall low RMSE values for both the output parameters also suggest that these values can be effectively applied in various rock engineering problems with reliable confidence.
- Limitation: the analysis results are applicable only for rocks under very low confinement and free of moisture.

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