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Prediction of the uniaxial compressive strength of rocks from simple index tests using a random forest predictive model

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Abstract. Uniaxial compressive strength (UCS) is an important mechanical parameter for stability assessments in rock mass engineering. In practice, obtaining the UCS simply, accurately and economically has attracted substantial attention. In this paper, studies related to UCS estimation using indirect tests were reviewed, it was found that regression techniques and soft computing techniques were mainly used to evaluate the UCS value, and theses soft computing techniques can accurately and effectively predict the UCS. To select the proper indirect parameters to predict the UCS, statistical analysis was performed on the relationships between UCS and indirect parameters, and based on the analysis, two indirect parameters (the Schmidt hammer rebound value (L-type) and ultrasonic P-wave velocity) were deemed adequate to predict UCS. To establish the UCS predictive model, the random forest algorithm was employed, the predictive model was verified by data collected from references. To further verify the validity of the predictive model, laboratory tests were performed, and the predictive results were consistent with the measured results, thus the UCS value predictive model can be applied to the fields of rock mechanics and engineering geology.

Keywords. Uniaxial compressive strength (UCS), Indirect tests, Statistical analysis, Random forest algorithm.

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1. Introduction

Uniaxial compressive strength (UCS) is the parameter most commonly used [1] to assess the stability in rock mass engineering. In practice, proper determination of the UCS of rock is of critical importance in the design of geotechnical engineering structures, the UCS is a key parameter in deformation analysis and gives a good estimation of the rock bearing capacity. Conversely, inappropriate estimation of the UCS could be catastrophic, as this situation can lead to underestimation of the ultimate bearing capacity and the loading corresponding to an allowable settlement for a problem of interest. To accurately, effectively and economically obtain the UCS value, the UCS testing procedure has been standardized by ASTM International (formerly known as the American Society for Testing and Materials) [2] and the International Society for Rock Mechanics (ISRM) [3, 4]. Although, the testing method is simple, performing a direct test to measure the UCS of rock is relatively expensive and time consuming [5, 6, 7], furthermore, preparing the required rock core or cubic sample is often difficult, especially for rocks that are highly fractured, thinly bedded, or block-in-matrix [8, 9, 10]. Due to these reasons, uniaxial compressive tests have been usually replaced by indirect, simpler, faster and more economical tests [11, 12], these indirect tests include Schmidt hammer tests, point load strength tests, etc. These indirect tests are very easy to carry out because they necessitate less or no sample preparation, and the testing equipment is less sophisticated; furthermore, the use of indirect methods is inexpensive and flexible [13]. Therefore, many attempts have been made to develop different kinds of techniques for estimating UCS.

The indirect techniques for the evaluation of UCS can be generally classified into two categories: the regression techniques (Table A1) and the soft computing techniques (Table A2). Empirical formulas can be determined by using regression techniques because that the empirical formulas can be easily applied to practice; hence, regression techniques have been commonly used by researchers, and empirical formulas have been frequently used to predict UCS. With the development of computer science, different kinds of soft computing techniques have been developed. Soft computing techniques can accurately and effectively predict UCS. However, different kinds of soft computing techniques have different characteristics, and selecting the proper soft computing technique is critical for UCS prediction.

1.1. *Regression techniques*

In 1964, D'Andrea *et al.* [14] proposed an empirical expression describing the correlation between UCS and point load strength ($I_{s(50)}$), which is the first time that the UCS value was calculated using the indirect parameters. Subsequently, to more accurately estimate the UCS, the empirical formula for estimating UCS was revised [15, 16, 17, 18, 19, 20, 21]. Then, many other indirect rock property parameters were used to estimate the UCS, such as the impact strength index (ISI) [22] and Schmidt hammer rebound value (R) [15, 23, 24, 25, 26, 27, 28].

Due to the merits of indirect tests for estimating UCS, the ISRM proposed an empirical formula to estimate UCS values by using of $I_{s(50)}$ [29], which suggested that the use of indirect tests for estimating UCS value were officially accepted, greatly promoting the development of indirect tests for UCS. Many other empirical formulas were developed to estimate UCS [30, 31, 32, 33, 34, 35, 36, 37, 38, 39].

Conventionally, experimental data are collected from a series of experiments. Subsequently, to quantitively describe the correlations between UCS and other indirect parameters, regression techniques are used, and empirical formulas can be determined. The regression procedure fits a curve to the data set, which is computed by minimizing the squared deviations of the measured data to the curve. The line is defined by the relevant equation, and the fitting coefficient is determined. The fitting coefficient is an indicator of how well the empirical formula fits the data. Due to the simplicity of the application of empirical formulas in engineering practice, empirical formulas are widely used to depict the correlations of UCS with indirect parameters.

In these equations (Table A1), the linear empirical formula is commonly used [14, 16, 17, 18, 19, 20, 27]. On the one hand, the linear equation can be easily memorized and is convenient for use in engineering practice; hence, linear empirical formulas can be applied in situ due to simplicity. On the other hand, the linear equation is determined by a limited data set and limited rock types (1 rock type is commonly used); thus, the fitting coefficients of the empirical formulas are high. However, with increasing of the numbers of datasets and rock species, the fitting coefficients may decrease, the empirical formula may not be reliable, and the validity of these empirical formulas should be further verified. When different kinds of rocks were used, certain new empirical formulas were proposed [15, 23], for instance, Aufmuth [23] proposed an power equation type empirical formula, but the relationships between indirect parameters and uniaxial compressive strength cannot be simply summarized by linear equations any longer. Additionally, many other types of empirical formulas are listed in Table A1. The empirical formulas were usually determined for few types of rocks, which limits the application of these empirical formulas.

The empirical formulas were frequently established by using regression techniques based on the limited numbers of experimental datasets and rock types, which impeded the wide application of the empirical formulas. In addition, the types of empirical formula used were subjectively determined in most literature. Conventionally, different types of equations, such as linear, exponential, power, and logarithmic functions, were used to conduct the least squares fit. Then, the final empirical formula was determined based on the fitting coefficients; this method is a typical trial and error method. However, the trial and error method significantly depends on the experience of the researchers. Moreover, there are complicated nonlinear relationships between the UCS and indirect parameters, so it is difficult to use one empirical equation to accurately describe the relationships between UCS and indirect parameters. Although regression techniques can be easily applied to in situ engineering practice, the deficiencies of this technique are pronounced.

1.2. *Soft computing techniques*

In addition to the conventional regression techniques, different kinds of soft computing techniques have been applied to predict UCS (Table A2), such as artificial neural networks (ANNs) [13, 38, 40, 41, 42, 43, 44, 45, 46] and fuzzy inference systems (FISs) [5, 47, 48, 49, 50], etc. These soft computing techniques provide new alternatives for predicting UCS.

(1) Artificial neural networks (ANNs)

An ANN is a soft computing technique inspired by the information processing of the human-brain [51]. In essence, an ANN attempts to find a nonlinear relationship between certain input and output parameters [43]. An ANN includes at least three layers: an input layer, an output layer, and an intermediate or hidden layer(s) [13, 52]; each layer comprises one or more nodes (neurons), and the lines between the nodes indicate the flow of information from one node to the next node. The ANN algorithm has recently been used to evaluate geotechnical problems [13, 40, 53, 54, 44, 46, 55, 56, 57, 58].

Although ANN techniques can approximate any complex nonlinear function, this technique does suffer from certain disadvantages: ANNs can be trapped at local minima value and learn rather slowly [59]. The performance of an ANN is directly dependent on the architecture of the layers and the number of neurons, which is the pattern of the connections between the neurons [60], and numbers of layers and neurons are hard to determine in practice.

(2) Fuzzy inference systems (FISs)

The fuzzy set theory is the kernel of the FIS, this theory was introduced by Zadeh [61] and then became an important tool in various engineering modelling, replacing the traditional methods of designing and modeling of a system. Fuzzy set theory can be used to develop rule-based models that combine physical insights, expert knowledge, and numeric data in a transparent way and closely resemble the real world. Generally, fuzzy decision-making processes are similar to decision-making processes in the human mind which obtains an abundance of vague information, analyses the information, and make decisions [61].

An interesting and perhaps the most attractive characteristic of FIS compared with other soft computing techniques, such as neural networks and genetic algorithms, is that these systems are able to describe complex and nonlinear multivariable problems in a transparent way. Moreover, fuzzy models can cope with nonprobabilistic (i.e., semantic) uncertainties which are common in rock engineering. Furthermore, fuzzy rules may be formulated on the basis of expert knowledge of the system.

However, fuzzy logic and fuzzy inference systems involve too many fuzzy rules, which are difficult to deal with in practical cases where variability exits; these systems are not convenient or easily applied in practice.

(3) Hybrid algorithms

Due to the drawbacks of ANNs and FISs, certain new hybrid algorithms were developed to predict UCS, such as adaptive neuro-fuzzy inference systems (ANFISs) and particle swarm optimization - artificial neural networks (PSO-ANNs).

ANFIS was developed by Jang [62] based on the Takagi-Sugeno fuzzy inference system (FIS). An ANFIS is constructed by a set of if-then fuzzy rules with proper membership functions to produce the required output from the input data. As a universal predictor, ANFIS has the capability of estimating any real continuous functions [63]. An ANFIS model offers the advantages of both ANN and FIS principles and has all the benefits of these systems in a single framework; this model involves numbers of nodes connected by directional links, where each node is designated using a node function with fixed or changeable parameters. This soft computing technique has been extensively used in the field of geotechnical engineering [5, 47, 64, 65, 66].

PSO-ANN is a hybrid algorithm that combines an ANN and a particle swarm optimization (PSO). Although most complex nonlinear functions can be implemented by ANNs, these functions suffer from certain disadvantages: these functions can be trapped at local minima and learn rather slowly [59]. The PSO algorithm is an evolutionary population-based computation method for solving optimization problems [67, 68]. Many studies have shown the utility of particle swarm optimization techniques for improving ANN performance [60, 67, 69].

Many other soft computing techniques have been widely applied to the UCS prediction, these techniques will not be discussed individually in our paper. The superiority of soft computing techniques over regression techniques for UCS prediction can be attributed to the ability of soft computing techniques to capture the non-linear features and generalize the structure of the input variables and UCS. Soft computing techniques are feasible, quick and promising tools for solving engineering problems [70, 47, 71, 72, 73, 74].

Compared with regression techniques, soft computing techniques can be accurate and effective; however, certain limitations should be properly addressed: the hyper parameters in the algorithm are hard to choose, and the predictive results are remarkably influenced by the parameters. Hence, choosing a proper algorithm to predict UCS is critically important.

1.3. *Objectives of this paper*

The aim of this paper is an efficient predictive model for the UCS of rock materials. First, the correlation coefficients between UCS and indirect parameters were calculated, and the advantages and disadvantages of indirect tests for estimating UCS were discussed in detail. According to the correlated coefficients and analysis, the proper indirect parameters to estimate UCS were determined. To predict UCS accurately, a predictive model based on the random forest algorithm was established. To verify the validity of the predictive model, the model was confirmed by data collected from references and laboratory tests. However, certain other topics, such as the specific mechanisms related to the index effects on the UCS of rocks, were not specifically discussed in our study.

2. Suggested parameters for predicting UCS values

From the analysis of the characteristics of regression techniques and soft computing techniques, soft computing techniques outperform the regression techniques in UCS evaluation. Hence, in this section, a soft computing technique called the random forest algorithm was used to predict UCS. Before establishing the predictive model, the indirect parameters used for predicting UCS should be determined.

2.1. *Description of collected data*

Before the statistical analysis, the related data were collected. In this paper, more than 2000 groups of data were collected from more than 50 references, and a corresponding database was constructed, which is listed in an attachment (data_collected.xls). Additionally, the experimental data were obtained from different kinds of rocks, such as granite, tonalite, marble, chalk, basalt and limestone, which guarantees the validity of the predictive model for different kinds of rocks. The basic information of the collected data was tabulated in Table A3.

2.2. *Suggested indirect parameters*

With regard to UCS prediction, the indirect parameters directly influence the precision of UCS. In this section, proper indirect parameters are determined from correlated coefficients, and the difficulty of determining the indirect parameters is discussed.

Based on the data collected, the correlated coefficients can be calculated based on (1).

$$\rho(X_{\text{indirect}}, Y_{\text{UCS}}) = \frac{\operatorname{Cov}(X_{\text{indirect}}, Y_{\text{UCS}})}{\sqrt{D(X_{\text{indirect}})D(Y_{\text{UCS}})}} \tag{1}$$

where $\rho(X_{\text{indirect}}, Y_{\text{UCS}})$ is the correlated coefficient between the UCS and the indirect parameter, $\operatorname{Cov}(X_{\text{indirect}}, Y_{\text{UCS}})$ is the covariance coefficient between the UCS and the indirect parameter X_{indirect}, $D(X_{\text{indirect}})$ is the variance of the parameter X_{indirect}, and $D(Y_{\text{UCS}})$ is the variance of the UCS. Based on (1), the correlation coefficients between the UCS and indirect parameters are demonstrated in Figure 1.

As illustrated in Figure 1, it is obvious that the absolute values of the correlation coefficients of UCS with ρ, H_{A}, I_{d}, V_{s}, ISI are lower than 0.6, indicating that these parameters are relatively weakly correlated with UCS. Hence, in practice, the predicted UCS would not be very accurate if these indirect parameters were used. However, in certain references, the predictive models or empirical formulas can accurately predict UCS with higher fitting coefficients when using these indirect parameters, which is mainly because the experimental data and rock types were limited. Through analysis of the correlated coefficients between the UCS and the indirect parameters, these parameters should be carefully adopted to predict UCS.

Although very strong correlations were found between some indirect parameters (DUW, n_{e}, n, BTS, BPI, $I_{\text{s(50)}}$) and UCS, these parameters are hard to determine in practice; therefore, these

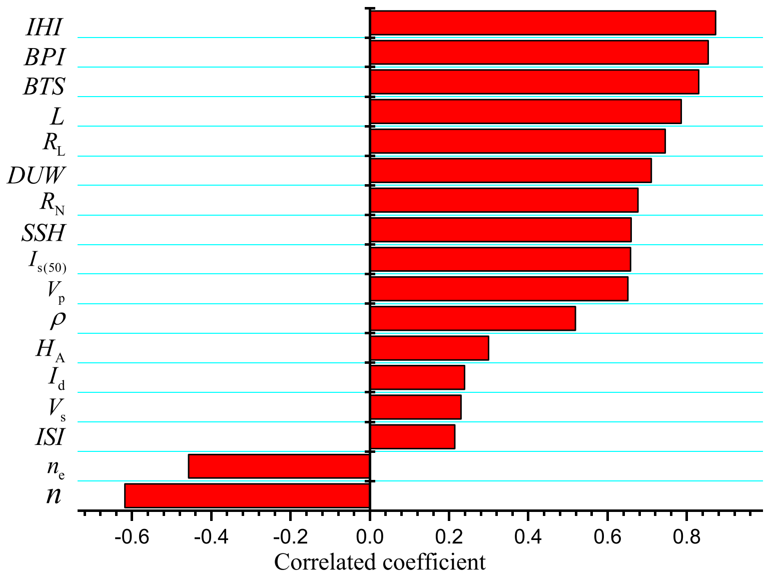


Figure 1. Correlation coefficients between the UCS and different kinds of indirect parameters (IHI: indentation hardness index, BPI: block punch index, BTS: Brazilian tensile strength, L: Equotip hardness, R_L: Schmidt hammer (L-type) rebound, DUW: dry unit weight, R_N: Schmidt hammer (N-type) rebound, SSH: shore scleroscope hardness, $I_{s(50)}$: point load strength, V_p: ultrasonic P-wave velocity, ρ: density, H_A: abrasion hardness, I_d: slake durability index, V_s: ultrasonic S-wave velocity, ISI: impact strength index, n_e: effective porosity, and n: total porosity).

parameters are not recommended. For example, the correlated coefficient between UCS and BTS is 0.83; however, to determine the BTS of rock, well-prepared core sample specimens are required. Compared with uniaxial compressive tests, the implementation procedure of Brazilian disc tests is not at all easy. From the aspect of obtaining these indirect parameters, the indirect parameters DUW, n_e, n, BTS, BPI and $I_{s(50)}$ are not recommended for predicting the UCS of rocks.

Furthermore, certain new indirect parameters such as SSH, IHI, L were used to estimate UCS in practice. These indirect parameters are highly correlated with UCS and the experimental procedures for determining these parameters are not difficult; however, the correlated coefficients of these parameters were calculated based on limited data, and very limited research has been reported in the literature regarding the application of these parameters for estimation of UCS. The validity of predicting UCS by these parameters needs to be verified. For example, the correlated coefficient between UCS and L was calculated based on 33 datasets, though the correlated coefficient is large, the applicability of L to predict UCS should be verified by more physical experiments. For accurately predicting the UCS, the validity of these parameters for predicting UCS needs to be further confirmed. Hence, in this study, these parameters were not used to evaluate the UCS.

The correlated coefficients were different when different types of Schmidt hammers type (L-type and N-type) were used. When the L-type Schmidt hammer type is used, the corresponding correlated coefficient is larger. Furthermore, the ISRM [75] suggests that the L-type hammer should be used for the hardness characterization of rocks, and the N-type Schmidt hammer is not endorsed by the ISRM for rock characterization. Hence, in practice, the L-type Schmidt hammer type was preferred, and in our paper, L-type Schmidt hammer rebound value was used to predict

UCS value.

V_p can be easily determined and it is significantly correlated with UCS. Additionally, this parameter has been commonly used to predict UCS. Hence, the V_p was suggested for prediction of UCS.

After the comprehensive consideration and analysis above, two parameters were finally selected for prediction of UCS: R_L and V_p.

3. UCS values prediction based on random forest algorithm

The hyper parameters of conventional soft computing techniques (such as ANNs, FISs and hybrid algorithms) are hard to determine; additionally, the predictive accuracy of these techniques is significantly influenced by the hyper parameters. However, the random forest algorithm (RF) is very different from conventional soft computing techniques (ANN, FIS, ANFIS, PSO-ANN etc.), this model is minimally influenced by the hyper parameters and has fast convergence speed. In addition, RF reportedly has the best prediction ability. Further, compared with ANN and FIS, the random forest model is more resistant to overfitting and is insensitive to noise in the data [76]. Thus, the random forest was employed to construct the UCS predictive model.

3.1. *UCS values prediction model based on random forest algorithm*

The random forest algorithm was developed by Breiman [77] to perform regression, classification and prediction. The RF UCS predictive model proposed in this paper is based on the construction of a large set of random trees during model training, leading to a single prediction. Additionally, to increase the diversity of the trees, each tree is constructed using a different bootstrap sample from the original data. Approximately one-third of the cases are left out of the bootstrap sample for error estimation, i.e., out of bag (OOB). This method has proven to be unbiased and accurate in error estimation [77, 78, 79]. The best split of each node of the tree is only searched for among a randomly selected subset of the total number of predictors, and the final prediction in the regression case is the average of the individual tree.

As a tree-based model, RF has advantages over linear models such as multinomial logistic regression: RF is able to model nonlinear relationships between predictors and response variables to handle noise data (observations with missing covariate data) and other situations in which a small dataset is associated with a large number of covariates [80]. Furthermore, individual decision trees tend to overfit, while bootstrap-aggregated (bagged) decision trees combine the results of many decision trees, reducing the effects of overfitting and improving generalization.

Due to the merits of the RF algorithm, this algorithm has already been widely used in the scientific community for different topics, such as digital mapping [81, 82], ecology [83, 84], chemistry and biology [77, 85]. However, RF is relatively new for rock mechanics engineering.

For convenient RF implementation, the main procedure of RF is described as follows.

1. The hyper parameters in the RF predictive model are determined: the number of split points, the depth of the tree, the number of trees, the number of sampling data points and the number of validating data points.
2. n groups of sampling data are randomly selected to construct a boosting tree.
3. A boosting prediction tree is established.
4. Step 2 and 3 are repeated m times, and m predictive trees are constructed.
5. m trees form the random forest, and the predicted value is the average of the individual tree predictive values.
6. Stop.

Table 1. Total of 477 datasets were selected for establishing a boosting tree

Number	1	2	3	4	5	6	7	......	477
R_{L}	5.17	11.50	11.67	11.96	13.99	14.13	14.86	......	72.00
UCS (MPa)	7.29	5.50	4.70	2.86	4.13	5.70	16.13	......	193.33

As stated above, the overfitting problem was overcome by establishing m trees. The RF predictive model consisted of many boosting trees; hence, establishing boosting trees is the key problem of the RF predictive model. The procedure of establishing a boosting tree can expressed as follows.

1. The training data set $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, $x_i \in X \subseteq R^n$, $y_i \in Y \subseteq R^n$ is determined. The initiation boosting tree can be expressed as $f_0(x) = 0$.
2. The residual of the boosting tree is calculated, based on the following equation.

$$r_{mi} = y_i - f_{m-1}(x_i), i = 1, 2, \ldots, N \tag{2}$$

The boosting tree can be expressed as:

$$f_m(x) = f_{m-1}(x) + T(x; \Theta_m) \tag{3}$$

$f_{m-1}(x)$ is the current boosting tree, and Θ_m is the parameter of the boosting tree, which is determined by next boosting tree $f_m(x)$ when the best value is obtained for the following equation.

$$\hat{\Theta} = \arg\min_{\Theta_m} \sum_{i=1}^{N} L(y_i, f_{m-1}(x_i) + T(x_i; \Theta_m)) \tag{4}$$

3. The boosting tree $f_m(x) = f_{m-1}(x) + T(x; \Theta_m)$ is updated, and the residual value of $f_m(x)$ is calculated.
4. The procedure is repeated for M times.
5. The boosting tree $f_M(x) = \sum_{m=1}^{M} T(x; \Theta_m)$ is obtained.
6. Stop.

From analysis of the procedure of the random forest algorithm, the theory of the RF algorithm is relatively simple. Furthermore, the convergence of the algorithm is not greatly influenced by the hyperparameters, and the hyperparameters do not influence the accuracy of the predictions, hence, this algorithm is quite easily applied in practice [86, 87, 88, 89, 90].

To illustrate the implementation of the RF predictive model more clearly, the use of the Schmidt rebound value (L-type) R_{L} to predict UCS is taken as an example.

1. The hyperparameters of the RF prediction model were determined. The number of split points was 50, the depth of the trees was 20, the percentage of training data was 66.7%, the percentage of testing data was 33.3%, and the number of trees was 25. In this stage, the dataset of (R_{L}, UCS) was collected from the attachment data_collected.xls; a total of 716 datasets were collected. The minimum and maximum of R_{L} were determined to be 5.17 and 72.00, respectively. The split number of the dataset was 50. Thus, 50 split points of R_{L} were linearly generated: 5.1700, 6.5338, 7.8977, 9.2616, 10.6255, ..., 72.0000; the distances between any two neighbouring split points were same. In every boosting tree, 477 datasets were randomly selected for constructing the predictive model, and the remaining 239 groups were used for testing purposes.
2. A total of 477 (R_{L}, UCS) datasets were randomly selected from the (R_{L}, UCS) datasets to establish a boosting tree; the random selected data are listed in Table 1.

Table 2. Residual value for the predictive tree $f_1(R_L)$

Number	1	2	3	4	5	6	7	......	477
R_{L}	5.17	11.50	11.67	11.96	13.99	14.13	14.86	......	72.00
UCS (MPa)	7.29	5.50	4.70	2.86	4.13	5.70	16.13	......	193.33
Residual value of UCS (MPa)	−49.66	−51.45	−52.25	−54.09	−52.82	−51.25	−40.82	......	53.74

3. A boosting tree was constructed by using 477 datasets and 50 split points. The tree depth of the boosting tree was 20, and the initial boosting tree was $f_0(R_{\mathrm{L}}) = 0$.

Hence, the initial residual could be calculated based on the following equation.

$$r_i = UCS_i - f_0(R_{\mathrm{L}i}) \tag{5}$$

In the initial step, because $f_0(R_{\mathrm{L}}) = 0$, $r_i = UCS_i$.

Subsequently, a best split point s was found when the following equation reached a minimum.

$$m(s) = \min_s[\min_{c_1} \sum_{R_{\mathrm{L}i}\in R_{\mathrm{L}1}} (r_i - c_1)^2 + \min_{c_2} \sum_{R_{\mathrm{L}i}\in R_{\mathrm{L}2}} (r_i - c_2)^2] \tag{6}$$

where $R_{\mathrm{L}1} = \{R_{\mathrm{L}}|R_{\mathrm{L}} \leq s\}$ and $R_{\mathrm{L}2} = \{R_{\mathrm{L}}|R_{\mathrm{L}} > s\}$. Additionally, it can be easily obtained that $c_1 = 1/N_1(\sum_{R_{\mathrm{L}i}\in R_{\mathrm{L}1}} r_i)$ and $c_2 = 1/N_2(\sum_{R_{\mathrm{L}i}\in R_{L2}} r_i)$. Based on (6), the best split s was determined to be 59.9295. Then, the regression tree $T_1(R_L)$ could be expressed as:

$$T_1(R_L) = \begin{cases} 56.9598, & (R_L \leq 51.9295) \\ 139.5877, & (R_L > 51.9295) \end{cases} \tag{7}$$

Next, the boosting tree $f_1(R_L)$ could be determined.

$$f_1(R_L) = f_0(R_L) + T_1(R_L) \tag{8}$$

Hence, the boosting tree $f_1(R_L)$ could be expressed as follows.

$$f_1(R_L) = \begin{cases} 56.9598, & (R_L \leq 51.9295) \\ 139.5877, & (R_L > 51.9295) \end{cases} \tag{9}$$

Based on the boosting tree $f_1(R_L)$, the residual could be calculated based on the following equation.

$$r_i = UCS_i - f_1(R_{\mathrm{L}i}) \tag{10}$$

Finally, we obtained the residual value, which is listed in Table 2.

Based on the residual value in Table 2, the dataset (R_{L}, r_i) was used to obtain the next regression tree $T_2(R_L)$ and the best split point s based on (6). The corresponding residual value was also calculated. This procedure was repeated a total of 20 times (depth of tree) in total. Then, the boosting tree could be expressed as follows.

$$f_{20}(R_L) = \begin{cases} 12.72, & R_{\mathrm{L}} \leq 21.02 \\ 26.99, & 21.02 < R_{\mathrm{L}} \leq 30.85 \\ 51.01, & 30.85 < R_{\mathrm{L}} \leq 35.07 \\ 54.63, & 35.07 < R_{\mathrm{L}} \leq 37.88 \\ \ldots\ldots & \\ 175.61, & R_{\mathrm{L}} > 70.19 \end{cases} \tag{11}$$

Based on the boosting tree (11) and R_{L} value, the predicted UCS value could be easily determined. For example, when R_{L} is 23, the UCS predicted UCS was 26.99 MPa.

4. Steps 2 and 3 were repeated $m = 25$ times; then, 25 trees were constructed.
5. A total of 25 trees formed the random forest, and the predictive value was the average of 25 individual tree predictive values.

6. Stop.

In this paper, the R^2 was used to describe how well the RF predictive model predicts UCS.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (UCS_i - f(R_{\mathrm{Li}}))^2}{\sum_{i=1}^{n} (UCS_i - UCS_{\mathrm{mean}})^2} \tag{12}$$

where UCS_i is the measured UCS values, UCS_{mean} is the average of the measured UCS, $f(R_{\mathrm{Li}})$ is the predicted UCS using the RF predictive model, and n is the number of groups of validation data. Based on (12) and the RF predictive model, the R^2 was calculated to be 0.62, which indicated that the RF predictive model could satisfactorily predict the UCS.

3.2. *Suggested input variables*

Through the different combinations of two indirect input variables R_{L} and V_{p}, 3 kinds of input variable combinations can be formed. Similarly, based on the RF predictive model, the UCS can be predicted when the input variables are different. The calculation results are listed in Figure 2.

Based on the calculation results, the predictive accuracy varied when the indirect variables input differed. Hence, choosing proper indirect parameters as input variables is important. Based on the calculation results, when the input variables are (R_{L}) and (R_{L}, V_{p}), the predictive results are acceptably accurate. Hence, these kinds of input variables are suggested for engineering practice and can precisely predict the UCS. For further verification of the accuracy of the RF predictive model, we verified the predictive model in laboratory tests.

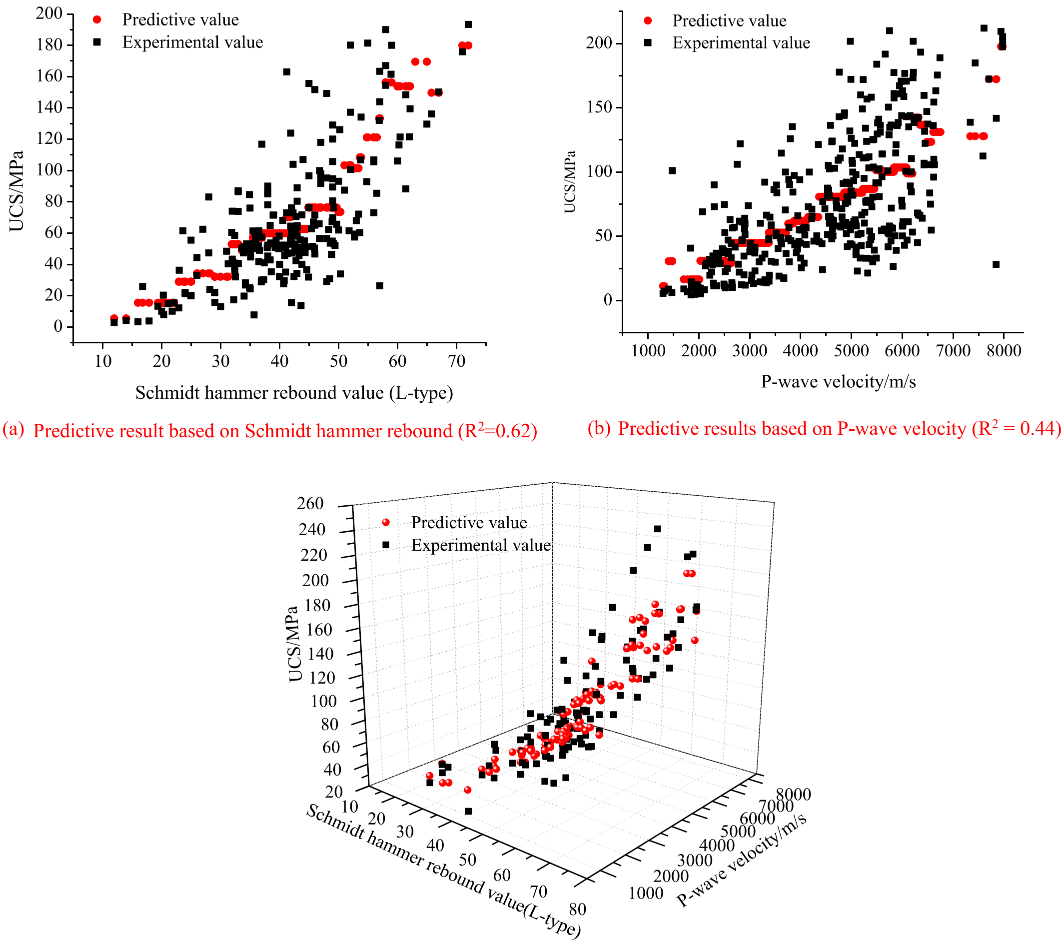
3.3. *Verification of the predictive model by laboratory tests*

To verify the capability of the RF predictive model, 8 types of rock (granite, yellow rust granite, red sandstone, Maokou limestone, skarn, marble, dunite, and amphibolite) were selected. A total of 5 rock specimens were prepared for each rock type, and the corresponding point load tests, ultrasonic pulse tests, Schmidt hammer rebound tests and uniaxial compressive tests were conducted.

Since ultrasonic pulse tests and Schmidt hammer tests are nondestructive, the specimens could be reused in our experiments. First, the ultrasonic pulse tests were performed firstly, then the Schmidt hammer tests and finally the uniaxial compressive tests. By using the experimental procedures, the specimens could be fully used.

3.3.1. *Ultrasonic pulse (P-wave) tests*

The dimensions of the test specimens' dimensions were Φ50 mm × 100 mm. Both faces of the core samples were trimmed and smoothed so the receiver and emitter could adhere to the core faces, and the direct transmission method was used to determine the P-wave velocity. A HS-YS4A test device was used to conduct the test. This device has one transmitter and one receiver that are 50 mm in diameter and have a maximum resonant frequency of 100 KHz. The wave velocity (V_{p}) was determined from the measured travel time and the distance between the transmitter and receiver in accordance with ASTM test designations [91]. The average of the 50 measurements was used.



(a) Predictive result based on Schmidt hammer rebound (R^2=0.62)

(b) Predictive results based on P-wave velocity (R^2 = 0.44)

(c) Predictive results based on Schmidt hammer rebound and P-wave velocity (R^2=0.73)

Figure 2. Predictive results for different kinds of input variables.

3.3.2. *Schmidt hammer rebound tests*

The HT-225B Schmidt hammer (L-type) was applied to obtain the Schmidt hammer rebound values, The Schmidt hammer tests were repeated 50 times for each specimen. The ISRM recommendations were applied to the tests for each specimen. The Schmidt hammer rebound values were recorded, and the average values were obtained.

To adequately secure the samples against vibration and movement during the tests, the rock cores were clamped. All the tests were implemented with the hammer held vertically downwards.

3.3.3. *Uniaxial compressive tests*

A New Sans Testing Machine was used to perform the uniaxial compressive tests. The loading rate was 100 N/s. The uniaxial compressive strength tests were performed according to the ISRM suggested methods [92].

The UCS can be calculated based on the following formula:

$$\sigma_{\mathrm{c}} = \frac{F}{A} \tag{13}$$

Table 3. Experimental results of laboratory tests for verifying the validity of the RF predictive model when the input variables are (R_L) and (R_L, V_p)

Specimen	R_L	V_p (m/s)	UCS (MPa)
Granite-1	66.5	6534.6	189.4
Granite-2	64.3	6341.0	177.8
Grainte-3	64.8	6667.1	184.6
Granite-4	66.0	6780.9	199.2
Granite-5	62.0	7556.7	197.4
Yellow rust granite-1	55.4	5055.1	123.6
Yellow rust granite-2	56.6	5961.0	137.8
Yellow rust granite-3	62.4	5523.0	149.8
Yellow rust granite-4	57.1	5108.6	141.3
Yellow rust granite-5	58.0	5566.7	134.6
Red sandstone-1	19.5	4268.6	24.6
Red sandstone-2	39.4	3693.0	53.0
Red sandstone-3	29.1	3413.7	39.5
Red sandstone-4	20.2	4234.1	23.2
Red sandstone-5	30.4	3079.2	37.3
Maokou limestone-1	50.2	4031.5	92.3
Maokou limestone-2	45.1	3363.2	67.6
Maokou limestone-3	49.1	4146.2	86.7
Maokou limestone-4	50.8	4865.9	97.2
Maokou limestone-5	48.7	4087.1	78.4
Skarn-1	51.5	4694.4	99.0
Skarn-2	52.7	4346.1	101.3
Skarn-3	45.5	4426.1	84.2
Skarn-4	53.9	5034.1	110.0
Skarn-5	47.5	4316.4	89.9
Mable-1	54.4	4505.5	111.8
Mable-2	46.9	5100.2	97.5
Mable-3	54.2	4254.4	99.1
Mable-4	45.2	5295.7	100.7
Marble-5	50.7	4883.7	102.7
Dunite-1	20.8	4347.4	30.2
Dunite-2	24.4	3190.4	26.2
Dunite-3	27.2	2652.2	27.2
Dunite-4	21.1	4755.5	29.9
Dunite-5	22.5	4474.8	29.7
Amphibolite-1	48.8	3321.1	70.1
Amphibolite-3	42.3	4638.8	76.1
Amphibolite-4	37.4	5094.9	75.2
Amphibolite-5	34.8	5444.0	72.1
Amphibolite-5	40.6	4856.7	79.9

where σ_c is the uniaxial compressive strength, F is the maximum failure load, and A is the section area of the specimens.

Table 4. Predictive results of the RF predictive model

Input parameters	R_L	R_L, V_p
R^2	0.89	0.90

3.3.4. *Laboratory test verification of the predictive models*

After conducting the experimental tests, the experimental results were obtained, which are listed in Table 3. In Table 3, the Schmidt hammer rebound (L-type), P-wave velocity and UCS are summarized, and these values were used to verifying the predictive model when the input variables are (R_L) and (R_L, V_p). Meanwhile, R^2 was used to describe how well the predictive model evaluated the experimental data. The calculation results are presented in Table 4. In the predictive model, the data collected from the references were taken as the training data, whereas the experimental data from laboratory tests were used for validation.

The model is excellent if R^2 is one. As listed in Table 4, the calculation results of R^2 indicated that the predictive UCS value appeared to be consistent with the measured UCS. Hence, the random forest predictive model can be applied to predict UCS. Based on the calculation results, the predictive accuracy is satisfactory for use in engineering practice use. Additionally, R and V_p should be within certain ranges, which are $5 < R < 70$ and $1000 < V_p < 9000$, respectively, because the datasets of R and V_p used in the predictive model are within these ranges. Additionally, the experimental data (R and V_p) for verifying the validity of the proposed RF predictive model are also within these ranges. When values of R and V_p are not within these ranges, the validity of RF predictive model needs to be further verified.

In summary, the RF predictive model can predict UCS in our tests with an appreciable degree of accuracy, and the RF predictive model provides high performance prediction capacity for the indirect determination of UCS. The RF UCS predictive model can be applied to practice when values of R and V_p are within the designated ranges.

4. Discussion

The UCS of rock is a critically important parameter for rock mass engineering stability analysis and rock mass design, particularly when the rocks are subjected to compressive stresses with low confining pressure [47]. Therefore, accurately and simply obtaining the UCS is of critical importance. There are generally two methods for the determination of the UCS: (a) direct laboratory tests on rock samples and (b) indirect estimations based on certain correlated parameters that can be obtained much more easily than the UCS itself. The direct laboratory tests require very strict conditions for preparing the rock specimens, which are difficult and sometimes even impossible to realize for cracked rocks. Moreover, direct measurement of UCS is expensive, time-consuming, and even infeasible in certain circumstances due to the difficulty involved in obtaining core samples [5, 93, 45, 54]. Subsequently, indirect estimation methods for UCS have been widely discussed for simplicity, and the estimation of UCS from simple tests has been investigated as an alternative of standardized UCS laboratory tests [28, 35, 94, 95].

In this paper, the references related to UCS prediction using indirect parameters were reviewed. Through analysis of the techniques predicting UCS. UCS estimation techniques can be generally divided into two categories: regression techniques and soft computing techniques. Previously, regression methods were adopted to establish empirical formulas, which are convenient for estimating UCS using indirect parameters. To obtain more accurate UCS, considerable efforts have been devoted to the empirical formulas to predict UCS for various rock types by linear regression analysis [96, 97, 50, 98, 99], multiple regression analysis [40, 45] and nonlinear regression models [39, 100, 101, 102, 103]. Conventionally, the empirical formulas were frequently determined by the experience of researchers. In the process of determining the empirical formulas, certain types of formulas were frequently used, such as linear, exponential, power, and logarithmic functions. Subsequently, the types of empirical formulas were determined according to the fitting coefficients; obviously, this process is not scientific. The empirical formulas were frequently determined with a limited number of types of rock and limited amounts of experimental data. As a result, the reliability and applicability of these empirical formulas are questionable.

Additionally, with the development of soft computing techniques, certain artificial algorithms have been applied to UCS values prediction. Analysis of the soft computing techniques shows that these soft computing techniques suitably predict UCS; however, the hyperparameters in soft computing techniques are hard to determine. Hence, selecting a proper computing algorithm for predicting UCS is important. In our paper, the RF algorithm was employed to predict UCS because this algorithm is able to model nonlinear relationships between predictors and is minmally influenced by the hyperparameters. Additionally, the predictive model requires shorter runtimes than other techniques because commonly used soft computing tools such as ANN and FIS rely on trial and error to optimize the model, which is a time-consuming.

For selecting proper indirect parameters to predict UCS, correlation analysis was conducted on the indirect parameters that were applied to UCS prediction; the difficulty in obtaining indirect parameters was also analyzed. Based on the analysis, two indirect parameters were selected to evaluate UCS values, i.e., the ultrasonic P-wave velocity and Schmidt hammer (L-type) rebound value. Subsequently, the RF algorithm was used to predict UCS, through the validation of collected data and laboratory tests; it was found that the RF predictive model is reliable and can be applied to practice, R and V_p should be within certain ranges when the proposed predictive model is applied to practice because the data for establishing the predictive model and the verification data are within the certain ranges.

Nevertheless, many other factors influencing UCS were not researched, such as the rock size and weathering effects. The RF predictive model is robust but difficult to physically explain and is incapable of revealing the mechanisms of the influences of the input variables on the UCS of rocks in this paper. These issues will be addressed in future work.

5. Conclusions

The UCS of rock is the most widely used design parameter in the general field of rock engineering. Based on the difficulty in obtaining the indirect parameters and the correlations of these parameters with the UCS, two indirect parameters were selected. The RF algorithm was used to predict the UCS. To verify the proposed predictive model, corresponding laboratory tests were performed. The prominent outcomes of this paper are summarized below.

(1) Through analysis of the correlations of different kinds of indirect parameters and the difficulty in determining the indirect parameters, two parameters, i.e., the Schmidt hammer (L-type) rebound and ultrasonic P-wave velocity, were recommended to predict UCS.

(2) Based on the RF algorithm, a UCS predictive model was established. The RF predictive model was verified by collected data. To further confirm the validity of the predictive model, laboratory tests were performed. The predicted UCS is consistent with the measured UCS. The predictive model is reliable when R and V_p are within the ranges of $5 < R < 70$ and $1000 < V_\mathrm{p} < 9000$, respectively. The RF predictive model can be applied to UCS prediction in engineering practice.

5.1. *Acknowledgments*

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Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

Appendix

Table A1. Empirical formulas for estimating UCS value

Researchers	Rock types	Empirical equations	R^2
D'Andrea *et al.*, 1964 [14]	-	$UCS = 15.3I_{s(50)} + 16.3$	-
Hobbs, 1964 [22]	-	$UCS = 53ISI - 2509$	-
Deere and Miller, 1966 [15]	Basalt, diabase, dolomite, gneiss, granite, limestone, marble, quartzite, rock salt, sandstone, schist, silt stone, tuff	$UCS = 20.7I_{s(50)} + 29.6$	0.92
		$UCS = 6.9 \times 10^{(0.16+0.0087(R\rho))}$	-
		$UCS = 1246R - 34890$	0.88
Broch *et al.*, 1972 [16]	-	$UCS = 23.7I_{s(50)}$	-
Aufmuth, 1973 [23]	25 different lithologies	$UCS = 6.9 \times 10^{(1.348\log(R\rho)-1.325)}$	-
		$UCS = 0.33(R\rho)^{1.35}$	-
Bieniawski, 1975 [17]	-	$UCS = 23I_{s(50)}$	-
Dearman and Irfan, 1978 [24]	Granite	$UCS = 0.0016R^{3.47}$	-
Beverly *et al.*, 1979 [25]	-	$UCS = 12.74e^{0.0185R\rho}$	-
Hassani *et al.*, 1980 [18]	Sedimentary	$UCS = 16I_{s(50)}$	-
Read *et al.*, 1980 [19]	Sedimentary rocks, basalts	$UCS = 16I_{s(50)}$ (sedimentary rocks)	-
		$UCS = 20I_{s(50)}$ (basalt)	-
Kidybinski, 1980 [26]	Coal	$UCS = 0.477e^{0.045R+\rho}$	-
Singh, 1981 [20]	-	$UCS = 18.7I_{s(50)} - 13.2$	-
Singh *et al.*, 1983 [27]	Coal	$UCS = 2R$	0.72
Forster, 1983 [21]	-	$UCS = 14.5I_{s(50)}$	-
Gunsallus *et al.* 1984 [96]	-	$UCS = 16.5I_{s(50)} + 51.0$	-
Sheorey and Kulhawy, 1984 [28]	Coal	$UCS = 0.4R - 3.6$	0.94
ISRM, 1985 [29]	-	$UCS = 20.25I_{s(50)}$	-
Haramy and DeMarco, 1985 [30]	-	$UCS = 0.994R - 0.383$	-
Ghose and Chakraborti, 1986 [31]	Coal	$UCS = 0.88R - 12.11$	-
Vallejo *et al.*, 1989 [32]	-	$UCS = 8.616I_{s(50)}$	-
O'Rourke, 1989 [33]	Anhydrite, siltstone, sandstone, limestone	$UCS = 4.85R - 76.18$	0.77
Cargill and Shakoor, 1990 [34]	Sandstone, limestone, dolomite, marble, synthetic, gneiss	$UCS = 23I_{s(50)} + 13$	-
Sachpazis, 1990 [35]	Carbonate rocks	$UCS = 4.29R - 67.52$	0.93
Xu *et al.*, 1990 [36]	Mica-schist	$UCS = 2.98e^{0.06R}$	0.95
Tsidzi, 1991 [37]	-	$UCS = 14.82I_{s(50)}$	-
Ghosh and Srivastava, 1991 [38]	Granitic rocks	$UCS = 16I_{s(50)}$	-
Grasso *et al.*, 1992 [39]	-	$UCS = 25.67(I_{s(50)})^{0.57}$	-
		$UCS = 9.30I_{s(50)} + 20.04$	-

Table A1. (Continued)

Researchers	Rock types	Empirical equations	R^2
Ulusay *et al.*, 1994 [97]	Sandstone	$UCS = 19I_{s(50)} + 12.7$	-
Chau and Wong, 1996 [104]	Granite, tuff	$UCS = 12.5I_{s(50)}$	0.73
Gokceoglu, 1996 [105]	Marl	$UCS = 0.0001R^{3.2658}$	0.84
Aggistalis *et al.*, 1996 [106]	Gabbro, basalt	$UCS = 1.31R - 2.52$	0.55
Kahraman, 1996 [107]	10 lithological units	$UCS = 4.5 \times 10^{-4}R^{2.46}$	0.93
Smith, 1997 [108]	Limestone, sandstone	$UCS = 14.3I_{s(50)}$	-
Tugrul and Zarif, 1999 [109]	Granite	$UCS = 8.36R - 416$	0.87
		$UCS = 35.54V_p - 55$	0.80
Katz *et al.*, 2000 [110]	Chalk, limestone, sandstone, marble, granite, syenite	$UCS = 2.208e^{0.067R}$	0.96
Sulukcu and Ulusay, 2001 [111]	23 samples in different rock types	$UCS = 15.31I_{s(50)}$	0.83
Kahraman, 2001 [112]	Dolomite, sandstone, limestone, marl, diabase, serpentine	$UCS = 6.97e^{0.014R\rho}$	0.78
		$UCS = 8.41I_{s(50)} + 9.51$	0.85
		$UCS = 9.95V_p^{1.21}$	0.83
Yilmaz and Sendir, 2002 [113]	Gypsum	$UCS = 2.27e^{0.054R}$	-
Quane and Russel, 2003 [100]	-	$UCS = 24.4I_{s(50)}$ (strong rocks)	-
		$UCS = 3.86(I_{s(50)})^2 + 5.68I_{s(50)}$ (weak rocks)	
Tsiambaos and Sabatakakis, 2004 [101]	Limestone, sandstone, marlstone	$UCS = 7.3(I_{s(50)})^{1.71}$	0.82
Yasar and Erdogan, 2004 [114]	Carbonate, sandstone, basalt	$UCS = 4 \times 10^{-6}R^{4.2917}$	0.98
Yasar and Erdogan, 2004 [115]	Lime, marble, dolomite	$UCS = (V_p - 2.0195)/0.032$	0.81
Palchik and Hatzor, 2004 [102]	-	$UCS = k_1 I_{s(50)} e^{-k_2 n}$	-
Dincer *et al.*, 2004 [116]	Andesite, basalt, tuffs	$UCS = 2.75R - 36.83$	-
Aydin and Basu, 2005 [117]	Granite	$UCS = 1.4459e^{0.0706R}$	0.92
Entwisle *et al.*, 2005 [118]	Volcanoclastic rocks	$UCS = 0.78e^{0.88V_p}$	0.53
Kahraman *et al.*, 2005 [119]	Basalt, andesite, granodiorite, granite, volcanic bomb, marble, serpentinite, gneiss, schist, migmatite, limestone, dolomitic limestone, sandstone, travertine	$UCS = 24.83I_{s(50)} - 39.64$ ($n < 1\%$)	0.84
		$UCS = 10.22I_{s(50)} + 24.31$ ($n > 1\%$)	0.75
Fener *et al.*, 2005 [120]	11 different rock samples	$UCS = 4.24e^{(0.059R)}$	-
Basu and Aydin, 2006 [121]	Granitic rocks	$UCS = 18I_{s(50)}$	0.97

Table A1. (Continued)

Researchers	Rock types	Empirical equations	R^2
Akran and Bakar, 2007 [122]	Sandstone, siltstone, limestone, dolomite, marl	$UCS = 22.791 I_{s(50)} + 13.295$	0.93
Shalabi *et al.*, 2007 [123]	Dolomite, limestone, shale	$UCS = 3.20R - 46.59$	0.76
Agustawijaya, 2007 [124]	39 samples in different rock types	$UCS = 13.4 I_{s(50)}$	0.89
Cobanglu and Celik, 2008 [125]	Sandstone, limestone, cement mortar	$UCS = 8.66 I_{s(50)} + 10.85$	0.87
		$UCS = 56.71 V_p - 192.93$	0.67
Sharma and Singh, 2008 [126]	Sandstone, basalt, phyllite, quartz mica schist, coal, shaly rock	$UCS = 0.0642 V_p - 117.99$	0.90
Kilic and Teymen, 2008 [127]	Different rock types	$UCS = 0.0137 R^{0.2721}$	0.93
Yilmaz and Yuksek, 2008 [40]	Gypsum rock samples	$UCS = 12.4 I_{s(50)} - 9.0859$	0.81
Yagiz, 2009 [128]	Travertine, limestone, schist, dolomitic limestone	$UCS = 0.0028 R^{2.584}$	0.92
Sabatakakis *et al.*, 2009 [129]	Marlstones, sandstone, limestone	$UCS = 13 I_{s(50)}$ ($I_{s(50)} < 2$ MPa)	0.70
		$UCS = 24 I_{s(50)}$ (2 MPa $< I_{s(50)} <$ 5 MPa)	0.60
		$UCS = 28 I_{s(50)}$ ($I_{s(50)} > 5$ MPa)	0.72
Diamantis *et al.*, 2009 [93]	Serpentinite rock	$UCS = 19.79 I_{s(50)}$	0.74
		$UCS = 0.11 V_p - 515.56$	0.81
Moradian and Behnia, 2009 [130]	64 different rock samples	$UCS = 165.05 e^{-4.452/V_p}$	0.70
Gupta, 2009 [131]	Granite	$UCS = 1.15R - 15$	-
Khandelwal and Singh, 2009 [132]	12 different rock samples	$UCS = 0.1333 V_p - 227.19$	0.96
Altindag and Guney, 2010 [133]	Different rock types including limestone	$UCS = 2.38 BTS^{1.0725}$	0.89
Torabi *et al.*, 2010 [134]	Siltstone, sandstone, shale, argyle	$UCS = 0.0465R^2 - 0.1756 I_{s(50)} + 27.682$	0.92
Yagiz, 2011 [135]	Travertine, mica schist, biotite schist, soft lime, dolomietic lime	$UCS = 0.258 V_p^{3.543}$	0.92
Kurtulus *et al.*, 2011 [136]	Ultrabasic rocks	$UCS = 0.0675 V_p - 245.13$ (accross foliation)	0.93
		$UCS = 0.0675 V_p - 245.13$ (along foliation)	0.83
Diamantis *et al.*, 2011 [137]	cement mortar	$UCS = 0.41 V_p - 899.23$	0.90

Table A1. (Continued)

Researchers	Rock types	Empirical equations	R^2
Farah, 2011 [138]	Weathered limestone	$UCS = 5.11BTS - 133.86$	0.68
Singh *et al.*, 2012 [41]	Quartzite, khondalite, sandstone, rock salt, shale, gabbro, amphibolite, epidiorite, limestone, dolomiete,	$UCS = 22.8I_{s(50)}$ (quartzite)	0.99
		$UCS = 15.8I_{s(50)}$ (Khondalite)	0.91
		$UCS = 21.9I_{s(50)}$ (sandstone)	0.89
		$UCS = 16.1I_{s(50)}$ (rock salt)	0.71
		$UCS = 14.4I_{s(50)}$ (shale)	0.82
		$UCS = 23.3I_{s(50)}$ (gabbro)	0.97
		$UCS = 23.5I_{s(50)}$ (amphibolite)	0.98
		$UCS = 21I_{s(50)}$ (epidiorite)	0.96
		$UCS = 22.3I_{s(50)}$ (limestone)	0.68
		$UCS = 22.7I_{s(50)}$ (dolomite)	0.82
Heidari *et al.*, 2012 [139]	Gypsum	$UCS = 10.99I_{s(50)} + 7.042$ (axial)	0.92
		$UCS = 11.96I_{s(50)} + 10.94$ (diametral)	0.94
		$UCS = 13.29I_{s(50)} + 5.251$ (irregular)	0.90
Mishra and Basu, 2012 [140]	Granite, schist, sandstone	$UCS = 14.63I_{s(50)}$	0.88
Kohno and Maeda, 2012 [141]	44 different rock samples	$UCS = 16.4I_{s(50)}$	0.85
Kahraman *et al.*, 2012 [142]	Different rock types including limestone	$UCS = 10.61BTS$	0.54
Khandelwal, 2013 [143]	12 samples of a wide rock type	$UCS = 0.033V_p - 34.83$	0.87
Minaeian and Ahangari, 2013 [6]	Conglomerate	$UCS = 0.005V_p$	0.94
Nazir *et al.*, 2013 [144]	20 limestone samples	$UCS = 9.25BTS^{0.947}$	0.90
Bruno *et al.*, 2013 [145]	Sedimentary carbonate rocks	$UCS = e^{2.28R-4.04}$	-
Saptono *et al.*, 2013 [146]	Wlarukin formation sandstone, mudstone (Turkey)	$UCS = 0.308R^{1.327}$	-
Kahraman, 2014 [7]	Pyroclastic	$UCS = 2.68e^{0.93I_{s(50)}}$	0.86
Mohamad *et al.*, 2015 [147]	40 samples of soft rocks	$UCS = 0.032V_p - 44.23$	0.83
Armaghani *et al.*, 2015 [148]	Granitic rocks	$UCS = 0.0308V_p - 61.61$	0.47
Kadir and Kesimal, 2015 [149]	-	$UCS = 0.1383R^{1.743}$	-
		$UCS = 0.097R^{1.8776}$	-
		$UCS = 4.2423R - 81.92$	-
Armaghani *et al.*, 2016 [150]	Granite, metamorphic, sedimentary rocks	$UCS = 11.442e^{0.0297R} + 0.001V_p^{1.178} + 22.297I_{s(50)} - 35.051$	-

Table A1. (Continued)

Researchers	Rock types	Empirical equations	R^2
Liang *et al.*, 2016 [151]	Sandstone	$UCS = 43.36DD + 11.161I_{s(50)} + 1.039R - 112.46$	-
Azimian, 2017 [152]	limestone	$UCS = 2.664R - 35.22$	-
		$UCS = 1.530R + 0.11V_p - 24.673$	-
Hebib *et al.*, 2017 [153]	limestone, sandstone, Dolomite, Calcareous tuff	$UCS = 2.855e^{0.0632R}$	-
Kong and Shang, 2018 [154]	Magnesian limesonte, woodkirk sandstone	$UCS = 1.80 \times 10^{-5} R - 5.5$(L-type)	-
		$UCS = 0.30R^{1.43}$ (N-type)	-

UCS: uniaxial compressive strength; $I_{s(50)}$: point load index; n: porosity; R: Schmidt hammer rebound value; ρ: density; V_p: P-wave velocity; k_1, k_2: empirical coefficient; a, b: constants; BTS: Brazilian tensile strength; ISI: impact strength index; DD: dry density; γ: unit weight; ISI: impact strength index.

Table A2. Soft computation techniques for predicting UCS value

Researchers	Input variables	Techniques	R^2
Garret, 1994 [70]	R, V_p, $I_{s(50)}$, n	ANN	-
Meulenkamp and Grima 1999 [13]	L, n, ρ, d	ANN	0.95
Singh *et al.*, 2001 [53]	PSV	ANN	-
Gokceoglu, 2002 [94]	PC	FIS	0.92
Gokceoglu and Zorlu, 2004 [5]	$I_{s(50)}, BPI, V_p, BTS$	FIS	0.67
Sonmez *et al.*, 2004 [11]	PC	FIS	0.64
Karakus and Tutmez, 2006 [155]	$I_{s(50)}$, R, V_p	FIS	0.97
Tiryaki, 2008 [156]	ρ, R, CI	ANN	0.40
Zorlu *et al.*, 2008 [42]	q, ρ, d, cc	ANN	0.76
Yilmaz and Yuksek, 2008 [40]	V_p, $I_{s(50)}$, R, I_d	ANN	0.93
Baykasoglu *et al.*, 2008 [54]	V_p, ρ, WA	GP	0.86
Yilmaz and Yuksek, 2009 [47]	V_p, $I_{s(50)}$, R, W_c	ANFIS	0.94
Gokceoglu *et al.*, 2009 [157]	CC, I_d	FIS	0.88
Canakci *et al.*, 2009 [158]	V_p, WA, ρ	GP	0.88
Dehghan *et al.*, 2010 [43]	V_p, $I_{s(50)}$, R, n	ANN	0.86
Cevik *et al.*, 2011 [159]	CC, I_d	ANN	0.97
Rabbani *et al.*, 2012 [44]	n, BD, S_w	ANN	0.96
Razaei *et al.*, 2012 [48]	R, ρ, n	FIS	0.95
Ceryan *et al.*, 2012 [45]	I_d, V_p, n_e, PSV	ANN	0.88
Yagiz *et al.*, 2012 [46]	V_p, n, R, ρ, I_d	ANN	0.50
Monjezi *et al.*, 2012 [9]	R, ρ, n	ANN-GA	-
Beiki *et al.*, 2013 [160]	ρ, n, V_p	GA	0.83
Yesiloglu-Gultekin *et al.*, 2013 [71]	BTS, V_p	ANFIS	0.68
Mishra and Basu, 2013 [49]	V_p, $I_{s(50)}$, R, BPI	FIS	0.98
Yurdakul and Akdas, 2013 [161]	R, SH, V_p	ANN	-
Manouchehrian *et al.*, 2013 [162]	n, ρ, CI, R, Q	GP	0.63
Ceryan, 2014 [163]	n, I_d	SVR	0.77
Torabi-Kaveh *et al.*, 2015 [164]	V_p, n, ρ	ANN	0.95

Table A2. (Continued)

Researchers	Input variables	Techniques	R^2
Mohamad *et al.*, 2015 [147]	BD, V_p, $I_{s(50)}$, BTS	PSO-ANN	0.97
Momeni *et al.*, 2015 [165]	R, ρ, V_p, $I_{s(50)}$	PSO-ANN	0.97
Armaghani *et al.*, 2016 [166]	R, V_p, $I_{s(50)}$	ICA-ANN	-
Fattahi, 2017 [95]	R	SVR-ABC	-
Heidari *et al.*, 2018 [50]	R, BPI, $I_{s(50)}$, V_p	FIS	0.91

R: Schmidt hammer rebound value; L: Equotip value; ρ: density; d: grain size; PSV: petrography study value; BPI: block punch index; BD: bulk density; S_w: water saturation; I_d: slake durability index; V_p: P-wave velocity; n_e: effective porosity; q: quartz content; n: porosity; $I_{s(50)}$: point load strength; W_c: water content; cc: concavo convex; PSV: petrography study values; PC: petrographic composition; CI: cone indenter hardness; CC: clay content; Q: quartz content; WA: water absorption; GA: genetic algorithm; PSO: particle swarm optimization; FIS: fuzzy inference system; ANN: artificial neural network; SVR: support vector regression; ABC: artificial bee colony algorithm; ICA: imperialist competitive algorithm; GP: genetic programming.

Table A3. Basic information of collected data

Researchers	Rock types	Indirect parameters	Number of data set
Tugrul and Zarif, 1999 [109]	Quartz monzonite, granite, tonalite	R, $I_{s(50)}$, V_p, n_e, n	19
Kahraman, 2001 [112]	Dolomite, sandstone, limestone, marl, diabase	R, $I_{s(50)}$, V_p, ρ, ISI	48
Yasar and Erdogan, 2004 [114]	Limestone, marble, sandstone, basalt	SSH	6
Palchik and Hatzor, 2004 [102]	Chalk	ρ, n	12
Dincer *et al.*, 2004 [116]	Basalt, andesite, tuff	DUW	24
Karakus *et al.*, 2005 [167]	Dacite, limestone, marble, listwanite	$I_{s(50)}$, V_p, n_e, ρ	9
Kahraman *et al.*, 2005 [119]	Basalt, andesite, granite, granodiorite, marble, limestone, sandstone, travertine	$I_{s(50)}$, n	38
Aydin and Basu, 2005 [117]	Granite	R, n_e, ρ, n	80
Fener *et al.*, 2005 [120]	Basalt, granite, andesite, marble, limestone, travertine	R, $I_{s(50)}$, ISI	11
Karakus and Tutmez, 2006 [155]	Dacite, limestone, marble	R, V_p	9
Buyuksagis and Goktan, 2007 [168]	Granite, marble, limestone	R	54
Shalabi *et al.*, 2007 [123]	Dolmite, shale, diopside	R, SSH, H_A	58

Table A3. (Continued)

Researchers	Rock types	Indirect parameters	Number of data set
Aoki and Matsukura, 2008 [169]	Tuff, sandstone, granite, andesite, limestone, dolomite, marble	n_e, L	33
Kilic and Teymen, 2008 [127]	Sedimentary, metamorphic rock	R, $I_{s(50)}$, V_p, n_e, SSH	19
Sharma and Singh, 2008 [126]	Sandstone, Greenish phyllite, quartz mica schist, coal, shaly rock	Id, V_p, ISI	48
Yagiz, 2009 [128]	Limestone, travertine, schist	V_p, ρ	9
Moradian and Behnia, 2009 [130]	Marlstone, sandstone, limestone	V_p, ρ, V_s	64
Diamantis *et al.*, 2009 [93]	Serpentinite	V_p, n_e, DUW, V_s	35
Kayabali and Selcuk, 2010 [170]	Gypsum, tuff, ignimbrite, andesite, sandstone, limestone, marble	R, $I_{s(50)}$	130
Torabi *et al.*, 2010 [134]	Coal	R	41
Dehghan *et al.*, 2010 [43]	Travertine samples	$I_{s(50)}$, V_p, n	30
Yagiz, 2011 [135]	Travertine, beige lime, dolomitic lime, soft lime, mica schist	V_p, ρ	9
Karakus, 2011 [171]	Granitic rocks	$I_{s(50)}$, V_p, n, BTS	19
Ceryan *et al.*, 2012 [45]	Carbonate rocks	Id, V_p, n_e, V_s, n	42
Heidari *et al.*, 2012 [139]	Rock samples from southeast of Gachasaran City, Southwest of Iran	$I_{s(50)}$	15
Gupta and Sharma, 2012 [172]	Pandukeshawar quartzite, tapovan quartzite, berinag quartzite	V_p, ρ, V_s, n	18
Singh *et al.*, 2012 [173]	17 rock samples	I_d, V_p, ISI	17
Singh *et al.*, 2012 [8]	Sandstone, rock salt, limestone, dolomite, amphibolite, quartzite, apidiorite	$I_{s(50)}$	11
Mishra and Basu, 2012 [140]	Granite, schist, sandstone	$I_{s(50)}$, BPI	60
Kahraman *et al.*, 2012 [142]	Basalt, andesite, volcanic bomb, granite, marble, limestone, travertine	BTS, IHI	46
Rezaei *et al.*, 2012 [48]	Diabase, gabbro, olivine, amphibolite, dunite, norite, granite	ρ, n	10
Nazir *et al.*, 2013 [144]	Limestone	BTS	20
Bruno *et al.*, 2013 [145]	Sedimentary carbonate rock	R	95

Table A3. (Continued)

Researchers	Rock types	Indirect parameters	Number of data set
Khandelwal, 2013 [143]	Rock mass samples were collected from different locations in India	R, I_d, V_p, ρ	12
Kumar *et al.*, 2013 [174]	Sandstone, ironstone, shell limestone, marl, shale	V_p, n_e, ρ	7
Yarali and Soyer, 2013 [175]	Quartzite, limestone, diabase, siltstone, granodiorite, basalt, marl	R, $I_{s(50)}$, SSH	32
Ng *et al.*, 2015 [176]	Granitic rocks	R, $I_{s(50)}$, V_p, n_e	115
Armaghani *et al.*, 2015 [148]	Granite	V_p, ρ	45
Torabi-Kaveh *et al.*, 2015 [164]	Limestone	V_p, n	20
Momeni *et al.*, 2015 [165]	Limestone, granite	R, $I_{s(50)}$, V_p, ρ	66
Mohamad *et al.*, 2015 [147]	Shale, old alluvium, iron pan	$I_{s(50)}$, V_p	40
Ataei *et al.*, 2015 [177]	Magnetite	R, V_p, n_e, V_s	11
Karaman and Kesimal, 2015 [149]	Limestone, basalt, dacite, metabasalt	V_p	46
Mishra *et al.*, 2015 [178]	Granite, schist, sandstone	$I_{s(50)}$, V_p, BPI	60
Tandon and Gupta, 2015 [179]	Granitoids, gneisses, metabasics, dolomite	R, $I_{s(50)}$, V_p	60
Kurtulus *et al.*, 2016 [180]	Kizaderbent volcanic, sopali arkose, korfez sandstone, derince sandstone, akveren limestone	$I_{s(50)}$, n_e, DUW	96
Armaghani *et al.*, 2016 [150]	Granite	R, $I_{s(50)}$, V_p	71
Ersoy and Acar, 2016 [181]	Granite	V_p	9
Armaghhani *et al.*, 2016 [182]	Granite	$I_{s(50)}$, V_p	124
Afoagboye *et al.*, 2017 [183]	granite gneiss, migmatite gneiss	R, $I_{s(50)}$	50
Akram *et al.*, 2017 [184]	Sakesar limestone	R, $I_{s(50)}$	42
Azimian, 2017 [152]	Limestone	R, V_p	30
Hebib *et al.*, 2017 [153]	Sandstone, carbonate rocks	R, n_e, ρ	19
Ghasemi *et al.*, 2018 [185]	Travertines, limestone	R, V_p, I_d, n_e, UW	10
Kong and Shang, 2018 [154]	Limestone, sandstone	R, $I_{s(50)}$	18
Heidari *et al.*, 2018 [50]	grainstone, wackestone-mudstone, boundstone, gypsum, and silty marl	$I_{s(50)}$, V_p, BPI	106

R: Schmidt hammer rebound value; $I_{s(50)}$: point load strength; V_p: ultrasonic P-wave velocity; I_d: slake durability index; n_e: effective porosity; UW: unit weight; BPI: block punch index; ρ: density; V_s: ultrasonic S-wave velocity; SSH: shore scleroscope hardness; ISI: impact strength index; L: equitip hardness; H_A: abrasion hardness; n: total porosity; DUW: dry unit weight; BTS: Brazilian tensile strength; IHI: indentation hardness index.

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