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PREDICTION OF UNCONFINED COMPRESSIVE STRENGTH OF ROCKS: A REVIEW PAPER

Ehsan Momeni, Ramli Nazir*, Danial Jahed Armaghani, Mohd For Mohd Amin, Edy Tonnizam Mohamad

Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

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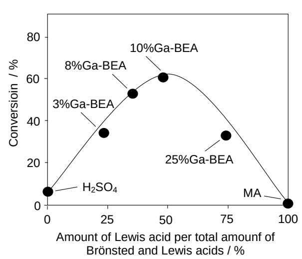
*Corresponding author
ramlinazir@utm.my

Graphical abstract



Abstract

Unconfined compressive strength (UCS) of rocks is a crucial parameter in designing geotechnical structures. Owing to difficulties in obtaining proper samples for UCS test as well as the point that conducting UCS is relatively expensive, the use of indirect methods for UCS estimation has drawn considerable attentions. This review paper is aimed to briefly highlight different proposed predictive models of UCS. In this regard, nearly 85 predictive models of UCS are listed in the paper which provides a good reference and database for geotechnical readers. The highlighted models are divided into two main sections. In the first section, UCS correlations with Brazilian tensile strength test, point load index test ($Is_{(50)}$), Schmidt hammer and ultrasonic velocity tests are highlighted. In the second section, recently proposed artificial intelligence-based predictive models of UCS are underlined. Apart from that, using available data (106 rock specimens), which were previously published by authors, a new correlation between UCS and $Is_{(50)}$ is developed which can be useful for assessing the UCS of tropical rocks. Overall, although the paper suggests conducting direct UCS test for important projects, based on the region and type of rocks, employing the highlighted predictive models for assessing the UCS of rock can be advantageous.

Keywords: Unconfined compressive strength, Brazilian tensile strength test, point load index test, Schmidt hammer, ultrasonic velocity, artificial intelligence

Abstrak

Kekuatan mampatan tak terkurung (UCS) batuan adalah parameter penting dalam mereka bentuk struktur geoteknik. Disebabkan kesukaran mendapatkan sampel yang betul untuk ujian UCS serta titik yang menjalankan UCS adalah agak mahal, penggunaan kaedah tidak langsung untuk UCS anggaran telah menarik perhatian yang besar. Kertas kajian ini bertujuan untuk mengetengahkan secara ringkas model ramalan yang berbeza daripada UCS. Dalam hal ini, hampir 85 model ramalan UCS disenaraikan dalam penerbitan yang menyediakan rujukan yang baik dan pangkalan data untuk pembaca geoteknikal. Model boleh dibahagikan kepada dua bahagian utama. Dalam bahagian pertama, korelasi UCS dengan ujian kekuatan tegangan Brazil, titik ujian indeks beban (IS50), penukul Schmidt dan ujian halaju ultrasonik dinyatakan. Dalam bahagian kedua, terkini telah dicadangkan ramalan menggunakan 'Artificial Intelligent' berdasarkan kepada UCS. Selain itu, dengan menggunakan data yang ada (106 spesimen batu), yang sebelum ini diterbitkan oleh penulis, hubungan baru antara UCS dan $IS_{(50)}$ dibangunkan yang membolehkan untuk menilai UCS batu tropika. Secara keseluruhan, walaupun kertas kerja ini mencadangkan untuk menjalankan ujian langsung UCS bagi projek-projek penting, berdasarkan keadaan kawasan dan jenis batu, penggunaan model-model ramalan yang digunakan untuk menilai UCS batu boleh memberikan lebih kebaikan.

Kata kunci: Kekuatan mampatan tak terkurung, ujian kekuatan tegangan Brazil, titik ujian indeks beban, penukul Schmidt, ujian halaju ultrasonik, artificial intelligence

1.0 INTRODUCTION

Unconfined compressive strength (UCS) of rocks is an important parameter in designing geotechnical structures. It reflects the bearing capacity of rocks. Although, direct determination of UCS is standardized by International Society for Rock Mechanics (ISRM) [1], many studies (see Tables 1 to 5) suggest the use of predictive models of UCS. It is generally attributed to difficulties in conducting UCS test as obtaining the proper rock samples more specifically in the case of weathered rocks is a difficult task. Additionally, the test is relatively time consuming and expensive. Therefore, developing indirect method of UCS estimation (predictive models) has drawn considerable attention. Predictive models are usually developed using regression analysis or artificial intelligence-based methods. In predictive models, results of one or more rock index tests, which are relatively quick, economic and easy to conduct tests, are used as model inputs in predictive models of UCS. Nevertheless, in the recent past years numerous models for estimating UCS of different types of rocks have been proposed (see Sections 2 and 3). It is due to the fact that rock behavior varies from a place to another place. Furthermore, repetition of this type of studies will constitute common sense and give broad observation chance about the relation between the prediction problem and the predictive methods. This paper is intended to review recently proposed correlations and models for UCS estimation as providing a list of them may be advantageous for geotechnical readers.

2.0 UCS ESTIMATION FROM BASIC ROCK TESTS

A review on past studies suggests that UCS of rocks is correlated with Brazilian tensile strength (BTS). BTS test is employed for indirect estimation of tensile strength and can be conducted according to the procedure suggested by ISRM [1]. Nazir *et al* [2] proposed a power equation for estimating UCS of limestone from BTS. According to their study, which was based on 20 sets of data, the reliability of their proposed equations in terms of R^2 is 0.90. Brady and Brown [3] reported that UCSs of rocks are approximately 8 times higher than their tensile strength. Nevertheless, Sheory [4] reported that strength ratio (UCS/BTS) values given in literature show a considerable variation (from 2.7 to 39.0). Table 1 shows some of the recently proposed correlation between UCS (MPa) and BTS. From this table, it can be understood that UCS of rocks is approximately 10 times higher than their BTS values. On the other hand, many researchers proposed correlations between UCS and point load index test ($Is_{(50)}$). Owing to its ease of use and simplicity of sample preparation, $Is_{(50)}$ test is used for indirect determination of UCS and it is standardized by ISRM [1]. A list of developed correlations between UCS and $Is_{(50)}$ is shown in Table 2. It is worth mentioning that the mode of failure in BTS test is different from UCS test. Therefore, as reported in Tonnizam Mohamad *et al* [5], it is generally expected to see that the UCS correlation with $Is_{(50)}$ is stronger than that of BTS. Using previously published data from studies conducted by Tonnizam Mohamad *et al* [5] and Momeni *et al* [6], a new correlation with R= 0.74 is proposed as shown in the following lines. The following equation was obtained based on the UCS and $Is_{(50)}$ tests results of 106 rock samples (see Figure 1). The proposed correlation is close to the well-respected correlation proposed by D' Andrea *et al*. [7]. Nevertheless, as shown in Table 2, developing correlations between UCS and $Is_{(50)}$ is more popular. This is attributed to the fact that point load test (like UCS test) is a destructive test in which rock samples fails under a compressive load. Therefore, the likelihood of having a better correlation with UCS is higher in comparison with other basic rock tests.

$$\text{UCS (MPa)} = 13.54\ Is_{(50)} + 14.93 \qquad (1)$$

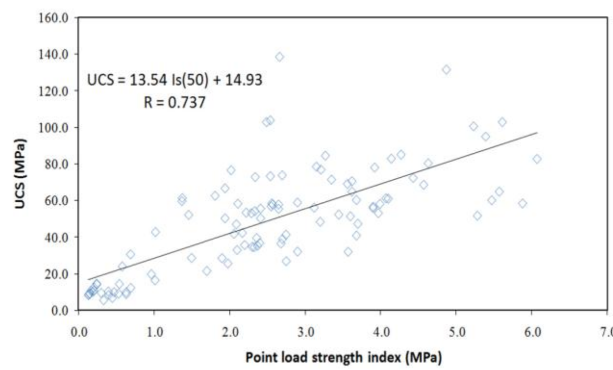


Figure 1 Proposed correlation between UCS and $Is_{(50)}$

Apart from the aforementioned destructive tests, the use of non-destructive tests such as Schmidt hammer and ultrasonic velocity, *Vp*, tests for indirect determination of UCS is underlined in numerous studies. The latter test indicates the state of compactness of the rock by measuring the velocity of primary wave which propagates through material texture of the rock. The former test also known as rebound test is a simple index test for estimating surface strength of rock samples. Nazir *et al*[b] [8] proposed an exponential equation for estimating the UCS of limestone using Schmidt hammer rebound number, R_L. In Table 3, a list of correlations which relates UCS to R_L is presented.

Additionally, numerous researchers addressed correlations between UCS and *Vp*. In Table 4, a number of these correlations (in different forms) are tabulated. It is interesting to note that as the sample size increases, the reliability of the correlations decreases. As shown in Table 4, when the sample size increases to 150 and 171, the reliability of the proposed equations decrease to R^2 = 0.67 and R^2 = 0.53. Therefore, it is suggested to not only look at the reliability of a proposed correlation but to consider the size of samples (dataset) which were used for developing that correlation.

Table 1 Suggested correlations between UCS and BTS

References	Correlations	R or R^2	Description
Kahraman *et al.* [14]	UCS = 10.61BTS	$R^2 = 0.54$	Different rock types including limestone
Farah [15]	UCS = 5.11BTS - 133.86	$R^2 = 0.68$	Weathered limestone
Altindag and Guney [16]	UCS = $12.38BTS^{1.0725}$	R = 0.9	Different rock types including limestone
Gokceoglu and Zorlu [17]	UCS = 6.8BTS +13.5	R = 0.65	-
Nazir *et al.* [2]	UCS = $9.25BTS^{0.947}$	$R^2 = 0.90$	20 Limestone samples
Karaman *et al* [18]	UCS = 24.301+4.874BTS	$R^2 = 0.90$	37 Rock samples including Basalt and limestone
Tahir *et al.* [19]	UCS = 7.53BTS	$R^2 = 0.44$	15 Limestone samples
Tugrul and Zarif [20]	UCS = 6.67BTS+4.67	-	19 Granite rock samples

Table 2 Suggested correlations between UCS and $Is_{(50)}$

References	Correlations	R or R^2	Description
Broch and Franklin [21]	UCS = 23.7 $Is_{(50)}$	-	-
Bieniawski [22]	UCS = 23 $Is_{(50)}$	-	Different type of rocks
Ghosh and Srivastava [23]	UCS = 16 $Is_{(50)}$	-	22 Granitic rock samples
Smith [24]	UCS = 14.3 $Is_{(50)}$	-	75 Samples (limestone and sandstone)
Kahraman [25]	UCS = 8.41 $Is_{(50)}$ + 9.51	R = 0.85	27 Different rock samples
Sulukcu and Ulusay [26]	UCS = 15.31 $Is_{(50)}$	R = 0.83	23 Samples in different rock types
Tsiambaos and Sabatakakis [27]	UCS = 7.3 $Is_{(50)}^{1.71}$	$R^2 = 0.82$	188 Samples (limestone, sandstone, and marlstones)
Kahraman *et al.* [28]	UCS = 10.22 $Is_{(50)}$ + 24.31	$R^2 = 0.75$	38 Different rock samples
Basu and Aydin [29]	UCS = 18 $Is_{(50)}$	$R^2 = 0.97$	40 Granitic rock samples
Agustawijaya [30]	UCS = 13.4 $Is_{(50)}$	$R^2 = 0.89$	39 Samples in different rock types
Yilmaz and Yuksek [31]	UCS = 12.4 $Is_{(50)}$ - 9.0859	$R^2 = 0.81$	39 Sets of gypsum samples
Diamantis *et al.* [32]	UCS = 19.79 $Is_{(50)}$	$R^2 = 0.74$	32 Samples of serpentinite rock
Kohno and Maeda [33]	UCS = 16.4 $Is_{(50)}$	R = 0.92	44 Different rock samples
Mishra and Basu [34]	UCS = 14.63 $Is_{(50)}$	$R^2 = 0.88$	60 Samples (granite, schist, and sandstone)
Tahir *et al.* [19] (2011)	UCS = 21.691 $Is_{(50)}$	$R^2 = 0.30$	15 Limestone samples
Singh and Singh [35]	UCS = 23.37 $Is_{(50)}$	R = 0.80	Quartzite rock samples
Tugrul and Zarif [20]	UCS = 15.25$Is_{(50)}$	R = 0.98	19 Granite rock samples
Basu and Kamran [36]	UCS = 11.103$Is_{(50)}$ + 37.66	R = 0.86	15 Schistose rock specimens
D'Andrea *et al.* [7]	UCS = 15.3$Is_{(50)}$ + 16.3	-	-
Fener *et al.* [37]	UCS = 9.08$Is_{(50)}$ + 39.32	R = 0.86	11 rock specimens
Basu [38]	UCS = 11.218$Is_{(50)}$ + 4.008	-	Schistose rocks
Li and Wong [39]	UCS = 19.83$Is_{(50)}$	-	Meta-siltstone
Kahraman [40]	UCS = 14.68$Is_{(50)}$ – 8.67	R = 0.88	32 Pyroclastic specimens
Chou and Wong [41]	UCS =12.5$Is_{(50)}$	R = 0.73	21 Hong Kong rock (granite and tuff) specimens
This study	UCS = 13.54 $Is_{(50)}$ + 14.93	R = 0.74	106 rock samples (limestone, granite, shale)

Table 3 Suggested correlations between UCS and R_L

References	Correlations	R	Description
Kilic and Teymen [42]	$UCS=0.0137R_L^{2.2721}$	0.93	Different rock types
Cobanoglu and Selik [43]	$UCS=6.59\ R_L\ -212.6$	0.65	Limestone, sandstone, cement mortar
Yasar and Erdogan [44]	$UCS=0.000004\ R_L^{4.29}$	0.89	Carbonates, sandstone, basalt
Tugrul and Zarif [20]	$UCS=8.36\ R_L\ -416$	0.87	19 Granite rock samples
Sachpazis [45]	$UCS=4.29\ R_L\ -67.52$	0.96	33 different carbonates
O' Rourke [46]	$UCS=4.85\ R_L\ -76.18$	0.77	Sandstone, siltstone, limestone
Singh *et al* [47]	$UCS= 2\ R_L$	0.86	Sandstone, siltstone, mudstone, seatearth
Ghose and Chakraborti [48]	$UCS=0.88\ R_L\ -12.11$	0.87	Coal
Xu *et al.* [49]	$UCS=2.98\ e^{(0.06\ RL)}$	0.95	Mica-schist
Aufmuth [50]	$UCS= 0.33(R_L\ \rho)^{1.35}$	0.80	25 different lithologies
Cargill and Shakoor [51]	$UCS= 18.17e^{(0.02\rho\ RL)}$	0.98	Carbonates
Haramy and DeMarco [52]	$UCS= 0.99\ R_L\ -0.38$	0.70	Coal
Nazir *et al.*[b] [8]	$UCS=12.83\ e^{(0.0487\ RL)}$	0.95	20 Limestone samples
Yurdakul *et al* [53]	$UCS = 0.0682R_L+57.973$	0.62	37 Carbonate rocks
Yilmaz and Sendir [54]	$UCS = e^{(0.82+0.06RL)}$	0.98	20 Gypsum rock samples
Minaeian and Ahangari [55]	$UCS=0.678R_L$	0.93	weak conglomeratic rock
Katz *et al.* [56]	$\ln(UCS)=0.792+0.067\ R_L \pm 0.231$	0.98	Limestone, sandstone and granite to name a few
Aydin and Basu [57]	$UCS=1.4459e^{0.0706\ RL}$	0.92	Granitic rocks
Gupta [58]	$UCS=1.15\ R_L\ -15$	0.95	Granite
Gupta [58]	$UCS=0.64\ R_L\ +37.5$	0.98	Quartzite
Gupta [58]	$UCS=14.1\ R_L\ -642$	0.89	Marble

*ρ is rock density

Table 4 Suggested correlations between UCS and V_P

References	Correlations	R or R^2	Description
Sharma and Singh [59]	$UCS = 0.0642V_P - 117.99$	$R^2 = 0.90$	49 samples in different rock types
Kahraman[25]	$UCS = 9.95\ V_P^{1.21}$	$R = 0.83$	27 different rock samples
Moradian and Behnia [60]	$UCS=165.05\exp(-4.452/Vp)$	$R^2 = 0.7$	64 different rock samples
Khandelwal [61]	$UCS = 0.033\ V_P - 34.83$	$R^2 = 0.87$	12 samples of a wide rock types
Khandelwal and singh [62]	$UCS = 0.1333\ V_P - 227.19$	$R^2 = 0.96$	12 different rock samples
Minaeian and Ahangari [55]	$UCS = 0.005\ V_P$	$R^2 = 0.94$	Some samples of weak conglomeratic rock
Diamantis *et al.* [32]	$UCS=0.11\ V_P - 515.56$	$R^2 = 0.81$	32 samples of serpentinite rock
Cobanoglu and Celik [43]	$UCS=56.71\ V_P - 192.93$	$R^2 = 0.67$	150 core samples of different rocks
Entwisle *et al.* [63]	$UCS= 0.78\ e^{0.88VP}$	$R^2 = 0.53$	171 samples of Volcanic rock
Tugrul and Zarif [20]	$UCS = 35.54\ Vp -55$	$R = 0.80$	19 Granite samples
Chary *et al.* [64]	$UCS = 0.1564\ VP - 692.41$	$R^2 = 0.80$	9 sandstone specimens
Goktan [65]	$UCS = 0.036\ Vp - 31.18$	$R^2 = 0.85$	-
Verma *et al.* [66]	$UCS= 0.008Vp+3.011$	$R^2 = 0.95$	15 coal samples (India)
Altindag [67]	$UCS = 12.743\ V_P^{1.194}$	$R = 0.76$	97 rock specimens (mainly limestone)

3.0 UCS PREDICTION USING ARTIFICIAL INTELLIGENCE

In the recent past years, the application of artificial intelligence (AI) in solving geotechnical problems has drawn considerable attention [9-11]. AI, which is a mathematical algorithm, can be employed in civil or geotechnical problems when the contact natures between some input(s) and output(s) parameters are unknown [12]. In general, it incorporates several techniques such as artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), particle swarm optimization (PSO), genetic algorithm (GA), a few of them are mentioned. Readers are referred to classic AI books for more information *e.g.* Englebrecht, [13]. This paper is not intended to provide details of AI techniques.

Nevertheless, for the problem of interest, there are several factors that can affect the UCS of rocks such as rock minerals, porosity, and water content to name a few. Hence, the use of AI in predicting UCS is advantageous. Many predictive models of UCS are highlighted in the literature.

Table 5 shows a list of the recently proposed AI-based predictive models of UCS. In this table, the model inputs as well as the reliability of the models are also tabulated. It should be highlighted that in developing any predictive model of UCS, there should be a meaningful relationship between UCS and input parameters. Another important point that deserves attention in evaluating the ANN-based predictive models is the number of input parameters, hidden nodes and layers. In this context, it is crucial to understand that increasing the number of input parameters and hidden nodes lead to higher number of free parameters and as consequence increases the model complexity. In other words, for constant sample size, the likelihood of model over-fitting is high when the number of hidden node or hidden layer increases; hence it is not surprising to see a high reliability. Apart from that, similar to regression analysis, the size of dataset should not be ignored in comparing different ANN-based predictive models of UCS. Due to lack of model generalization, predictive models which are developed using small dataset number (e.g. less than 30 according to Table 5) are not recommended.

Table 5 Recently proposed artificial intelligence-based predictive model of UCS

Reference	Technique	Dataset Number	Input Layer	R^2
Meulenkamp and Grimma [68]	ANN	194	L, n, ρ, d	$R^2 = 0.94$
Singh *et al*. [69]	ANN	112	PSV	-
Gokceoglu and Zorlu [17]	FIS	82	Is(50), BPI, V_p, BTS	$R^2 = 0.67$
Dehghan *et al*. [70]	ANN	30	V_p, Is(50), SR_n, n	$R^2 = 0.86$
Rabbani *et al*. [71]	ANN	-	n, BD, S_w	$R^2 = 0.96$
Rezaei *et al*. [72]	FIS	93	SR_n, ρ, n	$R^2 = 0.95$
Ceryan *et al*. [73]	ANN	55	n, I_d, V_m, n_e, PSV	$R^2 = 0.88$
Zorlu *et al*. [74]	ANN	138	q, pd, cc	$R^2 = 0.76$
Yilmaz and Yuksek [31]	ANFIS	121	Vp, Is(50), SRn, WC	$R^2 = 0.94$
Jahanbakhshi *et al*. [75]	ANN	133	ρ, n, Vp	$R^2 = 0.96$
Monjezi *et al*. [76]	ANN-GA	93	SRn, ρ, n	$R^2 = 0.96$
Yesiloglu-Gultekin *et al*. [77]	ANFIS	75	BTS, Vp	$R^2 = 0.60$
Beiki *et al*. [78]	GA	72	ρ, n, Vp	$R^2 = 0.91$
Momeni *et al*[a] [6]	PSO-ANN	66	SR_n, Vp, Is(50), ρ	$R^2 = 0.95$
Mishra and Basu [79]	FIS	60	Vp, Is(50), BPI, SRn	$R^2 = 0.98$
Torabi-Kaveh *et al*. [80]	ANN	105	Vp, ρ, n	$R^2 = 0.95$
Yagiz *et al*. [81]	ANN	54	Vp, n, SRn, Id, γ_d	$R^2 = 0.50$
Tonnizam Mohamad *et al*. [5]	ANN-PSO	40	Is(50), BD, V_p, BTS	$R^2 = 0.97$
Jahed Armaghani *et al* [82]	ANFIS	45	Vp, ρ, PSV	$R^2 = 0.98$
Jahed Armaghani *et al* [83]	ICA-ANN	71	n, Vp, SRn, Is(50)	$R^2=0.92$

BD: bulk density; BPI: block punch index; d: Grain size; GA: genetic algorithm; ICA: imperialist competitive algorithm; I_d: slake durability index; L: Equotip value; n: porosity; n_e: effective porosity; PSV: petrography study values; SRn: Schmidt hammer rebound number; S_w: water saturation, V_m: P-wave velocity in solid part of the sample; V_p: P-wave velocity ; WC: water content; γ_d: dry unit weight; ρ:density.

4.0 BRIEF DISCUSSION

As highlighted in previous sections, there are numerous well documented correlations between UCS and basic rock tests. In this study, correlations with even relatively low reliabilities are presented as they are based on real experimental data and most of them are well respected. It was discussed earlier that, in general, when the sample size, increases the likelihood of having correlations with higher reliability i.e. (R^2) decreases. Additionally, the UCS of rocks is not only related to BTS, Vp or R_L. Other parameters such as porosity, water content of rock sample (not necessary all the samples), existence of cracks in some of the rock samples due to weathering or sample quality can affect the reliability of a correlation. Therefore, it is not surprising to see correlations with relatively low or high R^2 in literature.In general such a variation is attributed to the complex and site-specific behavior of rocks. Needless to say that proper conducting of the related experimental tests (required for developing correlations) also has a direct effect on the reliability of a correlation. However, owing to the fact that basic rock tests are easy to perform, the likelihood of having low reliability solely due to improper conducting of the tests, at least in well established studies, is low. Overall, although the use of indirect methods of UCS estimation is advantageous, selecting a proper correlation is not an easy task and it depends to several factors such as sample (dataset) size, geographical area, and type of the rock. It was discussed earlier that rock behavior varies from a place to another place. For example, the use of the proposed correlation between UCS and $Is_{(50)}$ in this study may be advantageous for estimating the UCS of limestone in Malaysia (tropical region) but generalizing this correlation to other regions and/or other type of rocks is not recommended. Apart from that, the weathering grade of rocks is also of importance. For example, in the case of highly weathered rocks, the use of UCS-R_L correlations are not recommended mainly because in this case Schmidt hammer test is not a good representative of UCS. In fact, considering the diversity of the available correlations, one may conclude that for important projects relying on these correlations for UCS determination may not be reasonable and they can be used for assessing the UCS of rocks providing that the employed correlation is well established and respected.

5.0 CONCLUSION

85 predictive models of Unconfined Compressive Strength (UCS) with their reliability were highlighted in this paper which can provide a good reference for geotechnical readers. Additionally, using available data from authors` previous works, a new correlation between UCS and point load index test, $Is_{(50)}$ was proposed. The proposed correlation can provide a relatively good assessment of UCS of tropical rocks as it was based on a relatively large database.

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