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Prediction of the uniaxial compressive strength of sandstone using various modeling techniques

Danial Jahed Armaghani [a,*], Mohd For Mohd Amin [a], Saffet Yagiz [b], Roohollah Shirani Faradonbeh [c], Rini Asnida Abdullah [a]

[a] Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310, UTM, Skudai, Johor, Malaysia
[b] Department of Geological Engineering, Pamukkale University, Denizli, Turkey
[c] Young Researchers and Elite Club, South Tehran Branch, Islamic Azad University, Tehran, Iran

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ABSTRACT

Sandstone blocks were collected from Dengkil site in Malaysia and brought to laboratory, and then intact samples prepared for testing. Rock tests, including Schmidt hammer rebound number, P-wave velocity, point load index, and UCS were conducted. The established dataset is composed of 108 cases. Consequently, the established dataset was utilized for developing the simple regression, linear, non-linear multiple regressions, artificial neural network, and a hybrid model, developed by integrating imperialist competitive algorithm with ANN. After performing the relevant models, several performance indices i.e. root mean squared error, coefficient of determination, variance account for, and total ranking, are examined for selecting the best model and comparing the obtained results. It is obtained that the ICA–ANN model is superior to the others. It is concluded that the hybrid of ICA–ANN could be used for predicting UCS of similar rock type in practice.

1. Introduction

The UCS of rock is one of the significant parameters required for rock related engineering projects like excavation and tunneling. The test may be performed directly in the laboratory on rock sample which can be prepared and then tested according to international testing standards such as the American Society for Testing and Materials (ASTM) or International Society for Rock Mechanics (ISRM). Determining the UCS of rock in a laboratory is expensive, time consuming, and also needs well-prepared test sample which difficult to obtain for relatively weak rocks such as, shale, marl or sandstone. Because of these obstacles, predicting the UCS of rock is often interest of scientists dealing with engineering geology and rock mechanics. So, the UCS is traditionally estimated as a function of physical and mineralogical properties of rocks.

Many researchers have introduced empirical equations that is the result of simple or multiple regression analysis to estimate the UCS of various rocks.[1–14] These researches have been performed by using different rock type and rock properties; due to that, these empirical relations that depend on rock types may be vary. Further, multiple regression analysis technique which at least two input parameters is used for estimating the UCS of rocks.[16–20] Some of the milestone simple relationships between the UCS and relevant rock properties including the R_n, V_p, $I_{s(50)}$ published in the literature are given in Table 1.

Besides traditional empirical relations, various computer aid techniques including artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS), fuzzy logic (FL), fuzzy inference system (FIS), genetic algorithm (GA), particle swarm optimization (PSO) and also hybrid models like ANN-PSO have been performed to estimate the UCS of rocks.[35–45]

Further, imperialist competitive algorithm (ICA) which was introduced by Atashpaz-Gargari and Lucas[46] is a global search population-based algorithm. The ICA is an evolutionary computation that does not need the gradient of the function in its optimization process. Kaveh and Talatahari[47] applied the ICA to solve problem of skeletal structures. Nazari-Shirkouhi et al.[48] performed the ICA to solve the integrated product mix-outsourcing optimization problem. Taghavifar et al.[49] developed both ANN and the ICA–ANN systems to predict soil compaction indices. They successfully indicated that the network optimized by the ICA shows better performance in comparison with conventional ANN technique. Marto et al.[50] and Hajihassani et al.[51] integrated the ICA with ANN to optimize the ANN model for predicting environmental issues of blasting. They stated that hybrid model (ICA–ANN) is superior to other techniques (i.e., ANN).

In fact the ICA is recently introduced algorithm and yet no

* Correspondence to: Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia (UTM), 81310 Skudai, Johor, Malaysia.
E-mail address: danialarmaghani@gmail.com (D. Jahed Armaghani).

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Table 1
Various relationships between the UCS and R_n, V_p, $I_{s(50)}$ in the literature.

References	Relationship	R^2	Description
Aufmuth[1]	$UCS=0.33(R_n.\rho)^{1.35}$	0.80	25 different lithology
Singh et al.[2]	$UCS=2R_n$	0.86	Sandstone, siltstone, mudstone etc.,
Sachpazis[21]	$UCS=4.29R_n-67.52$	0.96	33 different carbonates
Xu et al.[22]	$UCS=2.98e^{(0.06\ Rn)}$	0.95	Mica-schist
Tugrul and Zarif [4]	$UCS=8.36R_n-416$	0.87	Granite
Kahraman[6]	$UCS=9.95V_p^{1.21}$	0.69	27 different rock samples
	$UCS=8.41I_{S(50)}+9.51$	0.72	
Sulukcu and Ulusay[5]	$UCS=15.3I_{S(50)}$	0.64	23 samples in different rock types
Yasar and Erdogan[7]	$UCS=0.000004R_n^{4.29}$	0.89	13 samples of various carbonate rock types
	$V_p=0.0317UCS+2.02$	0.64	
Tsiambaos and Sabatakakis[23]	$UCS=7.3I_{S(50)}^{1.71}$	0.82	188 samples (limestone, sandstone and marlstones)
Entwisle et al.[24]	$UCS=0.78e^{0.88Vp}$	0.53	171 samples of volcanic rock
Kahraman et al.[25]	$UCS=10.22\ I_{S(50)}+24.31$	0.75	38 different rock samples
Basu and Aydin[8]	$UCS=18I_{S(50)}$	0.97	40 granitic rock samples
Yilmaz and Yuksek[26]	$UCS=12.4I_{S(50)}-9.0859$	0.81	39 gypsum sample sets
Kilic and Teymen[10]	$UCS=0.0137R_n^{2721}$	0.93	Different rock types
Yagiz[17]	$UCS=0.0028R_n^{2.584}$	0.85	9 different rock types
Yagiz[11]	$UCS=0.258V_p^{3.543}$	0.92	9 different rock type, sedimentary and meta-sedimentary rocks
	$UCS=49.4V_p-167$	0.89	
Khandelwal and Singh[27]	$UCS=0.1333V_p-227.19$	0.96	12 coal samples
Moradian and Behnia[28]	$UCS=165\ \exp(-4.45/V_p)$	0.70	64different rock samples
Diamantis et al.[29]	$UCS=19.79I_{S(50)}$	0.74	32 samples of serpentinite
Mishra and Basu[30]	$UCS=14.63I_{S(50)}$	0.88	60 samples (granite, schist and sandstone)
Kohno and Maeda[31]	$UCS=16.4I_{S(50)}$	0.85	44 different rock samples
Khandelwal[32]	$UCS=0.033V_p-34.83$	0.87	12 samples of a wide rock types
Minaeian and Ahangari[33]	$UCS=0.005V_p$	0.94	Some samples of weak conglomeratic rock
Kahraman[13]	$UCS=2.68e^{0.93\ IS(50)}$	0.86	32 samples of pyroclastic rocks
Tonnizam Mohamad et al.[34]	$UCS=0.032V_p-44.23$	0.83	40 samples of soft rocks
Jahed Armaghani et al.[14]	$UCS=0.0308V_p-61.61$	0.47	45 samples of granitic rocks

R_n: Schmidt hammer Rebound Number; $I_{s(50)}$: Point load test; V_p: p-wave velocity; ρ: Density of the rock.

attempt made to estimate the UCS of rock using it or its hybrid. In the present study, several modeling techniques including LMR, NLMR, ANN and hybrid ICA–ANN, have been conducted to predict the UCS of rock by using rock properties including R_n, V_p, and $I_{s(50)}$. Furthermore, developed models are compared with several performance indices in accordance with their performance for practice.

2. Case study and data construction

An investigated area is located in Dengkil, Selangor, Malaysia, where are about 35 km to the south of Kuala Lumpur and 13 km to the north of Kuala Lumpur International Airport (KLIA). The area is under active development, and in fact, the data used for this study was collected for verifying the excavability of rock. The area composed of the Kenny Hill (KH) Formation[52] that is Carboniferous series. Sandstone, sedimentary, is the main rock type in the formation; however, phyllite, slate and shale are also locally observed in the field.

To obtain the aim of the study, more than 100 sandstone blocks samples were taken from the field and brought to the laboratory. Further, those blocks were cored and prepared to obtain the standard sample for individual test in accordance with International Society for Rock Mechanics.[53] Further, prepared samples are tested and the database is established. For each test, total 108 samples are prepared and the test including R_n, V_p, $I_{s(50)}$, and UCS was performed on them.

Sandstone, type of rock studied herein, displays typical granular texture with mineral grains size vary from 0.06 to 2 mm, and well cemented. Further, typical petrographic study has shown that the sandstone is composed of 85% mineral quartz and 15% clay as cement. The quartz is slightly fractured and exhibits sub-rounded to angular shape grains, traces of feldspars were also noted in the thin section of samples.

As a result of tests, the rock showed relatively low strength due to clay forming in their cement matrix. A range of (23.2–66.8 MPa) was obtained for UCS results which can be classified as medium to strong according to ISRM.[53] Also, obtained results can be classified as very low to low, in accordance with V_p (1.57–3.06 km/s).[54] The value of R_n and $I_{s(50)}$ ranges from 19-43 and 1.23–4.15 MPa, respectively. The results of R_n, V_p and $I_{s(50)}$ were utilized as input variables for generating the predictive models by using relevant modeling techniques. Afterward, the most acceptable and reliable model were chosen among them to introduce for practice.

3. Modeling techniques

3.1. Artificial neural network (ANN)

The ANN is first trained through processing numerous input patterns and corresponding outputs. The network is capable of recognizing similarities when they are presented with a new input parameter after appropriately predicting the output pattern. The ANNs can identify similarities in inputs, even though a certain input might never have been recognized until that time. Because of this property, it has excellent interpolation capabilities, in particular once input data is noisy (not exact).[55]

An ANN should be trained prior to the interpretation of new information. Although, there are several algorithms for training ANNs, back-propagation (BP) algorithm can be defined as the most versatile technique among them.[56] This algorithm makes available the most effective learning procedure for the multilayer neural networks. Due to the mentioned fact, BP is a well-known algorithm to train ANNs.[15,42,57]

Generally, the feed-forward BP includes three different layers i.e. input, hidden and output which are connected to each other. In fact, the outputs of neurons or nodes of the input layer are sent to nodes in hidden layer as input, and then by implementing similar procedure, they transfer to the last layer, which is output layer. The