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An ANN Approach for the Prediction of Uniaxial Compressive Strength, of Some Sedimentary and Igneous Rocks in Eastern KwaZulu-Natal

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Abstract

The Uniaxial Compressive Strength (UCS) of intact rocks is an essential index of strength in rock engineering. Laboratory based direct compressive strength estimation may be problematic, as obtaining fresh samples is not always feasible. Thus, the aim of indirect methods index test such as point load index test, and empirical correlations with UCS of indexes like the Brazilian indirect tensile strength test, serve as an alternative for many geotechnical engineering projects. The aim of this paper is to propose a relationship between UCS and indirect tests or indexes for some sedimentary and igneous rocks in KwaZulu-Natal using the technology of artificial intelligence. These tests include the point load index ($Is_{(50)}$) test and Brazilian Tensile Strength (σ_t), test. Block samples were collected in KwaZulu Natal, among these include sedimentary rocks (sandstones, siltstone, tillite) and igneous rocks (granitoids and dolerite). A back propagation artificial neural network was developed and trained in order to predict UCS. The input parameters were unit weight γ, ($Is_{(50)}$), (σ_t), and lithology. The lithology was introduced in the neural network as a qualitative input parameter, in order to indirectly incorporate in the model the mineralogical content. Training results returned, R value of 0.99% for the training set, and R = 0.92% for the test set, which is conveying to the conclusion that the approach is valid and could be used, as an alternative indirect approach to UCS estimation.

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Keywords: Uniaxial Compressive Strength; Point Load Index; Brazilian Tensile Strength; Artifical Neural Networks

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1. Introduction

Geotechnical design requires the estimation of intact rock properties. Strength of intact rock is a key parameter required in rock mass classification systems (RMR) [1], Q-system [2], and Hoek – Brown criterion [3]. Typically, the strength and the modulus of elasticity of intact rock can be determined by the unconfined compression test. This test is standardized by the International society for Rock Mechanics (ISRM 2007) [4]. Direct determination of these properties in the laboratory are complicated and often time consuming [5, 6]. Hence, the indirect estimation of UCS using rock index tests is of interest. The aim of this paper is the assessment of a relationship between UCS and indirect tests or indexes used to estimate the value of UCS based on data from sedimentary and igneous rocks in KwaZulu-Natal. These tests include the point load index (Is $_{(50)}$) test and the Brazilian Tensile Strength test. An artificial neural network was developed to predict a reliable UCS value. A back propagation ANN was developed and trained in order to predict UCS value based on blocks sample data from the (29) sedimentary and (14) igneous rocks. Among these 43 rock blocks samples were cored for the UCS, test, 129 for the point load test and 258 for the Brazilian test. The input parameters were unit weight γ, (Is $_{(50)}$), (σ_t), and lithology. The lithologies that are abundant in the KwaZulu-Natal province and were available for this study, are granitoid rocks, dolerite, sandstone, and tillite.

1.1. Previous studies

Point load index has long been regarded as the best intermediary for the UCS. It is relatively easy to conduct and economical, and thus widely applied both in the field and laboratory. Several authors have conducted ($I_{s\ (50)}$) and UCS tests for various lithologies to determine the most effective conversion factor which converts the ($I_{s\ (50)}$) to the representative UCS value [7–9]. It is evident from literature that the equations published exhibit a wide range, varying from linear to quadratic, and power laws. One of the problems commonly encountered is with the vast range of correlation equations offered in literature, there is often no agreement between authors on a specific conversion factor. Given the great variability of rock properties, even within the same lithology, it is consequently difficult, and often not very meaningful, to site specific values for specific rocks [10].

The Brazilian tensile strength has been widely used as an indirect test to measure tensile strength (σ_t). It has also been employed to produce estimates of UCS strength as these two parameters are commonly required and determined in most geotechnical projects [11]. As σ_t can be easily determined from the Brazilian tensile strength, it is useful to find strong conversion factors between these two parameters.

Generally these correlations give good results only in similar rocks [12]. According to [13] and later [14], the implementation of statistical prediction methods is not reliable if new available data are different from the original as the form of the obtained equation needs to be updated. According to Cilliers [15], the importance of the modeling complex systems through the use of ANN can be summarized in the ability to conserve the complexity of the systems they model because they have complex structures themselves. They also encode information about their environment in a distributed form and are capable to self-organize their internal structure. The application of artificial neural networks (ANN) techniques into the prediction of UCS, has been widely used in rock mechanics and in particular in the prediction of rock properties [16] and [17].

1.2. Artificial neural networks references from geotechnical applications of ANNs

Neural networks are one of the methods by which machines can learn. These machines are in general called as stimulus-response machines because of their fundamental operation: they can learn through exposure to a set of samples of inputs paired with the action that would be appropriate for each input. The perceptron was first conceived by Rosenblatt in (1958) [18], and is considered to be the ancestor of multi-layer perceptron. In multi-layer perceptron learning is achieved by adjusting weights in the network until its action-computing performance is acceptable, so that after the completion of the training procedure a particular input leads to a specific target output. Backpropagation Back – propagation algorithm (BP) is a non-linear extension of the least mean squares (LMS) algorithm for multilayer perceptron (MLP). It is the most widely used of the neural network paradigms and has been successfully applied in many fields of model free function estimation problems.

Success of artificial neural networks in various geotechnical engineering applications and in particular rock engineering, has already proven through the literature [19, 25].

Properly trained BP-ANN tend to produce reasonable results when presented with new data set inputs. BP-ANN is usually layered, with each layer fully connected to the layers below and above. The first layer is the input layer, the only layer in the network that can receive external input. The second layer is the hidden layer in which the processing units are interconnected to layers below and above. The third layer is the output layer. In Figure 1, the typical BP-ANN architecture is presented. Each interconnection has associative connection strength, given as weight. Weights are adjusted during training of the network. In BN-ANN training is supervised, in which case the network is presented with target, values for each pattern that are input. Input space is considered to be linearly separable. Transfer function is applied in order to find the best input output relation.

The equation of the transfer function, is given below:

$$f(x) = \frac{1}{1 + \exp^{(-ax)}} \tag{1}$$

where a is a slope parameter.

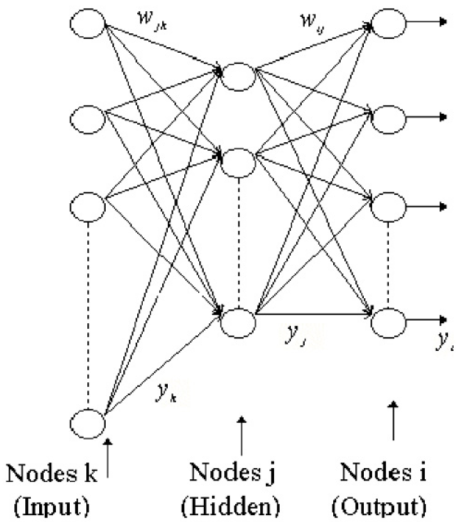

Fig. 1. A typical back-propagation network.

2. Data acquisition

Large blocks were collected from different localities within KwaZulu-Natal, South Africa. This allowed for reasonable spatial distribution as to provide representative samples. The granitoids and dolerite in this area are intrusive igneous rocks and form part of the Natal Metamorphic Province. The sandstones belong to the Newspaper Member and Kranskloof Member of the Mariannhill Formation, Natal Group. The upper portion of the Dwyka Group was also sampled. Two block samples of coarse grained sandstone from the Elliot Formation and fine grained sandstone from the Molteno Formation, were collected, (Appendix A.)

2.1. Laboratory tests

Coring and cutting of samples took place, and flattening of the ends of each sample perpendicular to the sample axis. The sides were checked and smoothed and polished. The samples were checked to ensure that there were free of cracks, fissures, and other discontinuities. Cylindrical cores were produced by coring using the Rothenberger Rodiadrill 1800 DWS. The cores were cut and grinded according to specifications for the different tests. Core samples were used to determine the unit weight (γ) as the intact strength of the core samples by performing (UCS), Point load test and Brazilian disc test. All tests were carried out according to the ISRM suggested guidelines [4].

UCS tests were conducted by means of the Servo-controlled compression testing machine, which has a load capacity of 2000 kN. The machine can apply compressive load at a constant strain rate on the specimen. In this study, all compression tests were conducted at strain rate equal to 0.5 mm/s. The 43 samples were prepared with a 2:1 L: D ratio.

The point load index test was conducted on 129 NX-size cores as well as block/irregular lumps of the rock samples using a point load testing machine in accordance to [4]. Three different tests were conducted to determine the PLI: axial, diametral and block/irregular lump, with samples being prepared according to [4] suggested methods for each type of point load test. The corrected index, ($Is_{(50)}$), is applied to obtain the unique Point Load Strength Index (PLI).

Brazilian test apparatus, which is equipped with a digital gauge unit, for displaying maximum load. A number of 258 test were performed were samples were taped and were placed on a specially fabricated steel cradle, and then mounted in between the loading platens. The procedure was repeated for all samples and the pressure at which the samples failed were recorded once failure occurred. Having the sample thickness (L) diameter (D) and maximum tensile load at failure (F), the Brazilian tensile strength (σ_t) is obtained by using the following equation by Gokhale (1960) [26], where (F) is the total force at failure, (D) the diameter of the core sample or the distance between conical heads of the testing machine, (L), Length or thickness of the rock specimen.

$$\sigma_t = \frac{2F}{\pi DL} \tag{2}$$

3. Data analysis using artificial neural network

The training dataset contains data for forty-six 43 full records. The lithology was introduced in the neural network as a categorical input parameter, in order for the model to incorporate the mineralogical content on the strength of the intact rock. A script was written in Matlab for the design of the architecture and training and of the artificial neural network. The data were normalized with respect to their maximum and minimum values. Trying to achieve the best network's performance, several networks with different architectures were developed. The number of hidden layers varied, the number of neurons both in the input and output layers changed, the training function and the training parameters have been altered. The final network architecture for the prediction of UCS consists of one input layer with 4 neurons one for each input parameter, one hidden layer consisting of 10 neurons and one output layer with a single neuron. The learning rate was set to lr = 0.02 and the error goal was set to eg = 0.01. In Figure 2 output values versus target values are presented. Whereas in Figure 3 the results of the ANN training for the training, validation and test set are presented, and network performance in Figure 4. Training results returned, R value of 0.99% for the training set, and R = 0.96% for the validation set, which is conveying to the conclusion that the approach is valid and could be used, as an alternative indirect approach to UCS estimation.

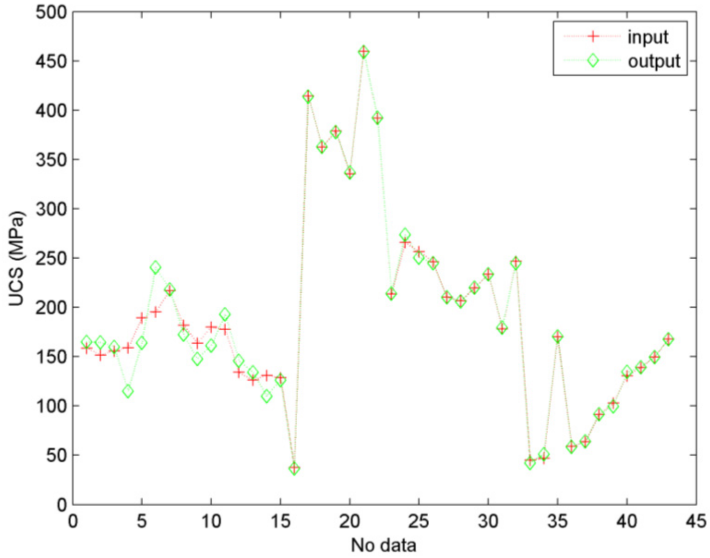

Fig. 2. Output values with (green-diamond) symbol, versus target values with (red-cross) symbol.

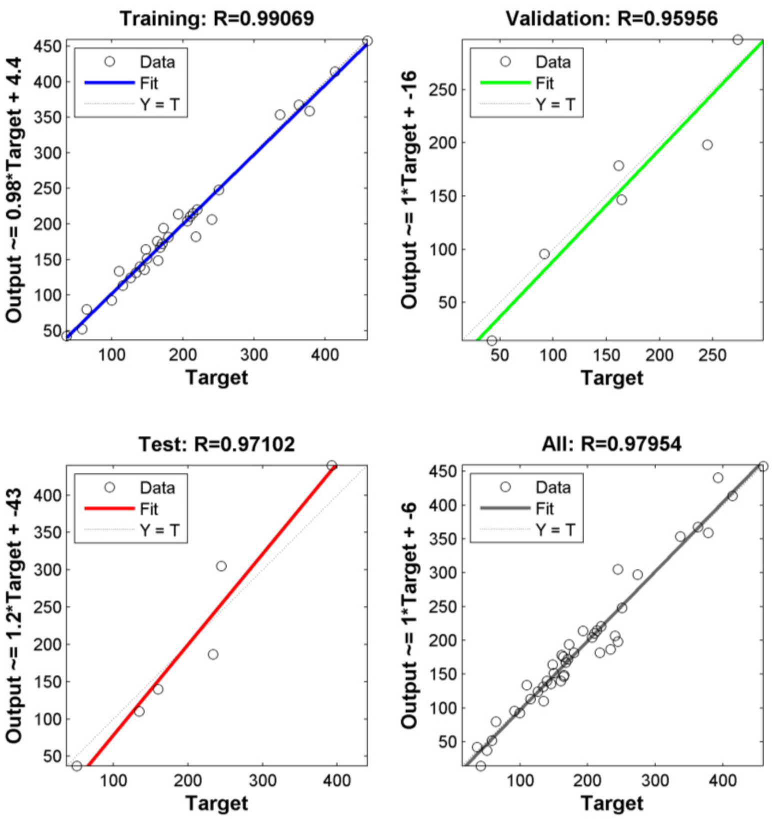

Fig. 3. Results of ANN training for the training, validation and test set.

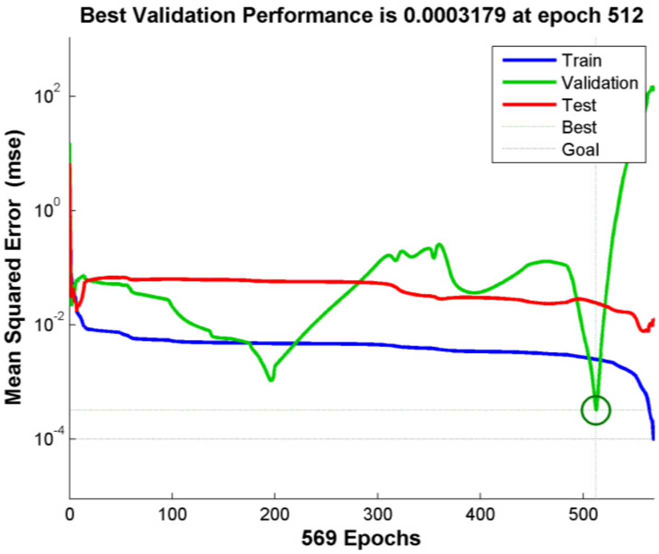

Fig. 4. ANN performance.

5. **Discussion and conclusion**

The main conclusions arising from the current study, is that the developed ANN allow for an initial reliable estimation of UCS. The proposed model using unit weight γ, point load index test (Is $_{(50)}$), tensile strength, and lithology to estimate UCS, suggests that could serve as a tool of reliable UCS prediction at the level of a feasibility study. The range of values measured under point load index tests and UCS present a correlation index of $R^2 = 0.70$.

Further systematic sampling from various other areas would allow for conducting of a greater programme of laboratory tests to increase the confidence in the proposed model and been able to generalise. Important parameters for rock engineering design such as Poisson ratio, Modulus of Elasticity, and others such as P wave velocity, and Schmidt hammer rebound number, could be measured in order to allow for the development of a complete database which would enable for further correlations among indexes and reliable estimations of UCS.

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Appendix A.

Table 1. Results of Laboratory tests conducted in this study.

No	CODE	γ dry	σt	PLI	Coded Lithology	Measured UCS	Predicted UCS	error	Formation
1	P1	26.30	2.86	2.30	2.00	165.00	160.20	4.80	Kranskloof Member sandstone
2	P2	25.86	2.63	3.10	2.00	164.40	140.43	23.97	Kranskloof Member sandstone
3	P3	25.63	2.63	4.10	2.00	160.05	142.13	17.92	Kranskloof Member sandstone
4	P5			3.30	2.00				Kranskloof Member sandstone
5	CD1	25.41	4.30	5.60	2.00	115.20	126.53	-11.33	Kranskloof Member sandstone
6	CD2	25.71	6.21	3.10	2.00	164.20	170.46	-6.26	Kranskloof Member sandstone
7	CD3	25.91	5.93	5.90	2.00	240.50	191.26	49.24	Kranskloof Member sandstone
8	CD4	25.82	6.20	4.40	2.00	218.20	209.52	8.68	Kranskloof Member sandstone
9	CD5		5.83	4.30	2.00				Kranskloof Member sandstone
10	CD6		5.50		2.00				Kranskloof Member sandstone
11	I1	26.04	4.83	6.00	2.00	172.30	189.91	-17.61	Newspaper Member sandstone
12	I2	26.15	4.13	3.10	2.00	147.90	172.78	-24.88	Newspaper Member sandstone
13	I3	26.11	4.75	6.50	2.00	161.40	176.35	-14.95	Newspaper Member sandstone
14	I4	26.24	4.68	4.20	2.00	193.10	201.94	-8.84	Newspaper Member sandstone
15	PR1	25.47	2.08	2.50	2.00	146.00	128.81	17.19	Newspaper Member sandstone
16	PR2	25.25	2.14	2.90	2.00	134.00	129.39	4.61	Newspaper Member sandstone
17	PR3	25.45	2.97	3.30	2.00	110.00	133.26	-23.26	Newspaper Member sandstone
18	PR4	25.18	2.50	3.70	2.00	126.50	122.87	3.63	Newspaper Member sandstone
19	PR5		3.34		2.00				Newspaper Member sandstone
29	D1	29.09	30.04	11.30	6.00	413.85	428.56	-14.71	Dolerite
30	D2	29.16	30.72	10.00	6.00	362.93	402.14	-39.21	Dolerite
31	D3	29.19	30.02	8.90	6.00	378.08	361.76	16.32	Dolerite
32	D4	29.22	30.09	8.90	6.00	336.64	359.49	-22.85	Dolerite

continued on next page

Table 1. Results of Laboratory tests conducted in this study (continued from previous page).

No	CODE	γ dry	σt	PLI	Coded Lithology	Measured UCS	Predicted UCS	error	Formation
33	D5	29.21	29.93	10.70	6.00	459.17	413.99	45.18	Dolerite
34	D6	29.21	29.50	9.40	6.00	392.49	377.32	15.17	Dolerite
35	Q1	25.55	16.19	6.39	2.00	213.89	216.34	-2.45	Natal
36	Q2	25.79	16.25	8.10	2.00	273.58	256.61	16.97	Newspaper Member sandstone
37	Q3	25.81	16.17	7.70	2.00	250.66	234.14	16.52	Newspaper Member sandstone
38	Q4	25.74	16.51	8.10	2.00	244.72	264.07	-19.35	Newspaper Member sandstone
39	DT1	23.57	15.59	5.70	5.00	210.26	209.30	0.96	Newspaper Member sandstone
40	DT2	24.95	15.35	5.50	5.00	206.24	203.73	2.51	Dwyka tillite
41	DT3	24.93	16.03	6.50	5.00	219.96	232.16	-12.20	Dwyka tillite
42	DT4	24.94	16.17	5.80	5.00	233.58	217.13	16.45	Dwyka tillite
43	DT5	24.94	16.34	5.84	5.00	179.73	219.87	-40.14	Dwyka tillite
44	DT6	24.94	16.21	6.10	5.00	244.80	224.80	20.00	Dwyka tillite
45	CS1	23.63	2.04	4.31	2.00	42.14	71.50	-29.36	Coarse grained sandstone Elliot formation
46	CS2	23.91	2.02	4.27	2.00	50.96	56.87	-5.91	Coarse grained sandstone Elliot formation
47	FS1	22.69	2.14	4.69	2.00	170.68	167.08	3.60	Fine grained sandstone Molteno formation
48	FS2	22.75		3.14	2.00	108.07			Fine grained sandstone Molteno formation
49	SB1a	24.33	8.22	3.97	3.00	58.41	55.48	2.93	Scotchborought granite
50	F1a	25.51	10.80	4.22	3.00	64.39	63.23	1.16	Fafa granitoid
51	F1b	25.60	8.83	4.09	3.00	91.85	30.82	61.03	Fafa granitoid
52	F1c	26.49	5.31	4.16	3.00	99.71	99.06	0.65	Fafa granitoid
53	F1d	27.17	5.06	4.34	3.00	134.67	169.68	-35.01	Fafa granitoid
54	WM1a	27.47	16.63	8.29	3.00	139.40	137.44	1.96	White Umfulozi granitoid
55	WM1b	27.47	12.90	5.65	3.00	149.74	155.58	-5.84	White Umfulozi granitoid
56	WM1c	28.74	13.81	4.64	3.00	167.67	165.57	2.10	White Umfulozi granitoid