Application of ANN & MVRA to Predict Uniaxial Compressive Strength and Modulus of Elasticity by Using Physical Properties of Limestone

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Abstract - *In mining, geomechanical properties like modulus of elasticity (E) and uniaxial compressive strength (UCS) are the two crucial design parameters as they represent the mechanical behaviour of rock. There are several direct procedures for UCS & E to determine in the laboratory, recommended by the ISRM and ASTM. These tests are relatively straightforward and reliable, but their prerequisite is high-quality sample preparation, well-calibrated equipment, and expertise to operate, are making the tests expensive with time-consuming, tedious work. Out of all these disadvantages, the indirect estimation of parameters has gained prominence. An attempt has been made to predict UCS & E from the physical properties of the limestone by using Artificial Neural Networks (ANN) and Multivariate Regression Analyses (MVRA). P-wave velocity, density, porosity, Schmidt hammer rebound value, slake durability index are used as input parameters, whereas UCS & E are output parameters to develop the ANN and MVRA models. The performance evaluation of all developed models are evaluated by statistical techniques like Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), Variance Accounted For (VAF), and Absolute Average Relative Error Percentage (AAREP), Coefficient of determination (R^2). On comparisons of performance indices, the ANN model has indicated high R^2, higher VAF, lower values of RMSE & AIC, and minimum value of AAREP than linear and non-linear multivariate regression analysis models for both UCS and E. The performance comparisons showed that neural networks are an effective and reliable approach for minimizing the uncertainties in predicting rock parameters.*

***Key Words*: Artificial Neural Networks, Multivariate Regression Analysis, Uniaxial Compressive Strength, Modulus of Elasticity, Limestone, Indirect estimation**

1.INTRODUCTION

The geomechanical properties of the rocks like uniaxial compressive strength and modulus of elasticity are the two crucial parameters widely used in designing rock engineering projects. Uniaxial compressive strength is included as the primary input parameter for the rock characterization, assessment and classification. Modulus of elasticity (E) is a character of rock materials, which estimates how carefully they approximate the perfect elastic material (Farmer, 1968; Jumikis, 1979). These laboratory investigations are standardized by the International Society for Rock Mechanics (ISRM, 2007). But still, there some limitations regarding the precision of the parameters (Wang, 1981). Some of the uncertainties in quantifying the rock parameters include sample preparation, testing environment, insitu moisture content, equipment calibration. Direct Determination of elastic properties in a laboratory is expensive, tedious, laborious, and very time consuming, as well as expertise is required (Palchik, 2007; Mishra and Basu, 2013; Wang and Aladejare, 2015, 2016). In most cases, due to difficulties in the preparation of high-quality core samples (weak, stratified, and highly fractured rocks) and test performance (time-consuming, expensive, and careful execution), UCS and E are not measured or ill measured by laboratory tests (Torabi-Kaveh et al.,2014). To overcome all these difficulties, some of the essential design parameters which are difficult to establish can be determined indirectly, using the relationship between the static and dynamic properties of rock with both statistical and artificial intelligence (AI) such as an artificial neural network (ANN).

Two crucial physical properties of rocks that have been utilised widely for the prediction of UCS and E are P-wave velocity (V_p) and porosity (n). There is a substantial relationship between these parameters as the V_p of a rock increases with decreasing effective porosity. Also, both the parameters powerfully correlate to the density (d) of considered rock. In this observation, many researchers have reported several relationships between UCS and E with Vp, d, and n in a simple or multivariate form (Minaeian and Ahangari 2013; Azimian and Ajalloeian 2015; Danial et al.2015; Abbaszadeh Shahri et al. 2016). Therefore, it can be noted that with these three parameters can be efficient and thriving in the prediction of UCS and E. Laboratory testing on the rock core samples is a very precise process in the estimation of rock strength. However, they cannot ever indicate the continuous profile of the formation, and Coring is comparatively very costly, and the results are susceptible to the rate of stress loading and unloading. Therefore, developing the prediction models for an indirect method of estimation has drawn considerable attention. Prediction models are developed using regression analysis (linear or non-linear) and artificial intelligence-built methods. In prediction models, the results of rock indexes, which are quick, highly economical and very easy to conduct the tests, are used as inputs in prediction models of UCS and E.

2. ABOUT THE STUDY AREA

The study area is located in Udaipur, Rajasthan, India. In a hand specimen, the sample is a medium-grained whitish limestone with slightly high silica content that is difficult to be distinguished from quartzite. At some places, the limestone is relatively complex and siliceous in nature, having more than 15% silica, mainly due to the presence of quartz and pegmatite along foliation planes. Bedding planes are found to be filled with grains of quartzite, quartz stingers and pegmatite. They are indicative of limestone with high silica and low total carbonate. There is no physical indication of the presence of magnesia in limestone patches. The limestone formation is traversed by the number of bands of pegmatite. Generally, they follow the bedding of schistosity of limestone with minor variation and never cut across. Geologically the area forms under the part of the Raialo series, A part of Archean Crystalline Complex. Underlain by Aravali supergroup System and over the line by the Delhi supergroup System. The main lithological unit includes Quartzites, phyllite, garnitiferous Biotite schist, Gneisses and limestone. Various acid and basic intrusions frequently traversed these formations. The limestone is white to buff white in colour, crystalline, banded and medium-grained to saccharoidal coarse-grained texture and associated with calc-silicate calc-granulates, acidic and basic intrusives of pegmatites and amphibolites.

3. LABORATORY INVESTIGATIONS AND DATA ANALYSIS

To provide an acceptable estimate of the overall properties of the limestone of the study area, the samples must be representative of the rock and its lithological variability. The core samples were randomly collected across the study area as the borehole samples represent the sequence and local facies variations, and then the obtained cores were prepared as required specimens by Core cutting and grinding machines for laboratory testing. The specimens were then prepared in the laboratory as per the ISRM standards designed to determine different physicomechanical properties. Before testing, the specimens were dried in the oven at a temperature of 105^{0}C for 24 hours to remove any moisture. Laboratory investigations were conducted as per international society for rock mechanics to determine P-wave velocity, density, porosity, Schmidt hammer rebound value, and Slake durability, Uniaxial Compressive strength and Modulus of Elasticity by as per (ISRM. 1978a, ISRM. 1979b, ISRM. 1981a. ISRM. 1981b.) The obtained results and their basic statistics are tabulated in Table 3.1. The UCS values of the collected rock samples ranged between 79.26 and 103.98 MPa, with an average value of 91.46 MPa. In contrast, the average value of E was 54.17 GPa values varied from 50.65 to 56.89 GPa.

4. DATA ANALYSIS

4.1 Linear Multivariate Regression Analysis

Multiple regression analysis is a powerful modelling technique that can be useful when complex relations are involved. The linear multivariate regression technique is used to unite two or more parameters that affect a rock property. This method can be beneficial in instances where complex relations are deeply involved. Moreover, multiple regression models' elastic properties of intact rocks would be accurately suggested because the obtained equations are accompanied by the determination coefficients (R^2). This test was performed at a 95 % significance level. A higher coefficient of determination would be desirable. In the present study, MVRA analysis was carried out to predict UCS & E by using V_p, d, n, SDI and SHRN.

Table 3.1: Basic Descriptive statistics of the data set

Description	Parameters						
	E (Gpa)	UCS (Mpa)	V_p (m/s)	d (kg/m^3)	n %	SDI	SHRN
Minimum	50.65	79.26	5,221.94	2,485.00	2.27	97.21	42.00
Maximum	56.89	103.98	5,509.68	2,943.00	2.56	99.95	52.00
Mean	54.17	91.46	5,370.01	2,731.70	2.36	98.85	47.33
Standard deviation	1.58	8.13	95.35	129.49	0.07	0.64	2.95
Mean standard error	0.25	1.29	15.08	20.47	0.01	0.10	0.47

Table 4.1: Descriptive statistics of linear MVRA for UCS and E

Dependent Variable	Independent variable	Coefficient	Std. error	T-value	Std. coefficients	R^2
UCS	Intercept	-360.1185	117.955	-3.053	--	0.850
	V_p (m/s)	0.0523	0.008	6.589	0.613	
	d (Kg/m³)	0.0003	0.005	0.055	0.005	
	n %	8.4103	4.195	2.005	0.077	
	SDI	1.0366	1.312	0.790	0.082	
	SHRN	1.0088	0.351	2.871	0.366	
E	Intercept	-239.9625	125.245	-1.916	--	0.709
	V_p (m/s)	0.0071	0.008	0.840	0.426	
	d (kg/m³)	-0.0084	0.006	-1.503	-0.686	
	n %	-3.3135	4.455	-0.744	-0.155	
	SDI	2.9716	1.393	2.133	1.199	
	SHRN	-0.1459	0.373	-0.391	-0.272	

The obtained Multivariate Regression equation for the prediction of UCS & E is given below in equation (4.1) & (4.2):

$$UCS = -360.118 + 0.0523\,V_p + 0.0003\,d + 8.41\,n + 1.036\,SDI + 1.008\,SHRN \quad (4.1)$$

$$E = -239.963 + 0.0071\,V_p - 0.0084\,d - 3.3135\,n + 2.9716\,SDI - 0.1459\,SHRN \quad (4.2)$$

Whereas UCS is the uniaxial compressive strength (MPa), Vp is the P-wave velocity (m/s), E is the modulus of elasticity (GPa), n is the porosity (%), d is the density (kg/m³), SDI is the slake durability index, SHRN is the Schmidt Hammer Rebound Number.

4.2 Non-Linear Multivariate Regression Analysis

The Non-linear multivariate regression technique is also employed to predict UCS and E. For establishing the statistic model, the same input variables used as inputs of linear multivariate statistics models consist of Vp, d, n, SDI, and SHRN were applied. The obtained Multivariate Regression equation for the prediction of UCS & E is given below in equation (4.3) & (4.4):

$$UCS = 3690.98 + 2.29\,V_p + 0.08\,d - 149.3\,n - 196.7\,SDI - 10.8\,SHRN - 0.0002\,V_p^2 - 0.00001\,d^2 + 32.02\,n^2 + 1.008\,SDI^2 + 0.12\,SHRN^2 \quad (4.3)$$

$$E = -19309.38 + 3.7\,V_p + 0.08\,d - 1684\,n + 234.36\,SDI - 20.31\,SHRN - 0.0003\,V_p^2 - 0.00002\,d^2 + 342.2\,n^2 - 1.16\,SDI^2 + 0.2\,SHRN^2 \quad (4.4)$$

Table 4.2: Descriptive statistics of non-linear MVRA for UCS and E

Dependent Variable	Independent variable	Coefficient	Std. error	R^2
UCS	Intercept	3690.979	9993.0	0.910
	V_p (m/s)	2.2907	1.2647	
	d (Kg/m³)	0.0807	0.18	
	n (%)	-149.345	623.58	
	SDI	-196.714	184.05	
	SHRN	-10.8683	8.56	
	V_p^2 (m/s)	-0.0002	0.0001	
	d^2 (Kg/m³)	0.0000	0.0000	
	n^2 (%)	32.0244	126.90	
	SDI^2	1.0077	0.9	
	$SHRN^2$	0.1213	0.08	
E	Intercept	-19309.3	10759	0.774
	V_p (m/s)	3.749	1.361	
	d (Kg/m³)	0.087	0.203	
	n (%)	-1684.0	672.72	
	SDI	234.365	198.12	
	SHRN	-20.311	9.196	
	V_p^2 (m/s)	0.000	0.000	
	d^2 (Kg/m³)	0.000	0.000	
	n^2 (%)	342.276	136.90	
	SDI^2	-1.169	1.008	
	$SHRN^2$	0.208	0.097	

Whereas E is the modulus of elasticity (GPa), UCS is the uniaxial compressive strength (MPa), d is the density (kg/m³), Vp is the P wave velocity (m/s), n is the porosity (%), SDI is the slake durability index, SHRN is the Schmidt Hammer Rebound Number. Table 4.1 & 4.2 shows the coefficients of the parameters and standard errors along with the coefficient of determinations for linear and non-linear MVRA models

4.2 Artificial Neural Network Analysis

Multi-layer perceptrons (MLP's)are the layered feedforward architectured networks that are trained with backpropagation techniques. These networks can be implemented in acquiring pattern classification. The main advantage of multi-layer perceptrons is that they are effortless, flexible and secure to use. These models consist of three layers of neurons. The first layer is an input layer. It is used to present data to the network. The input layer receives the data from various sources. Hence, the number of inputs decides the total size of individual neurons in the network's input layer. The second layer is a hidden layer(s). These are employed to perform as an assemblage of pattern detectors. In ANN algorithms, the construction of network architecture requires the optimal number of hidden layers between the input layer and output layer and the optimal number of neurons in each layer. The total number of hidden layers and their neurons is often determined by the trial-and-error method. The third layer is an output layer. It produces an suitable response in the form of output to the given input data. The output layer consists only a single node that represents UCS or modulus of elasticity (E).

In the present study, Levenberg–Marquardt is applied to identify and train the network. In this neural model, an activation function has been used, which is Tan Sigmoid. Furthermore, Levenberg-Marquardt is used as a learning rule. A three-layer artificial neural network with the description of input and output nodes employed in this study is shown in Fig. 4.1 & 4.2

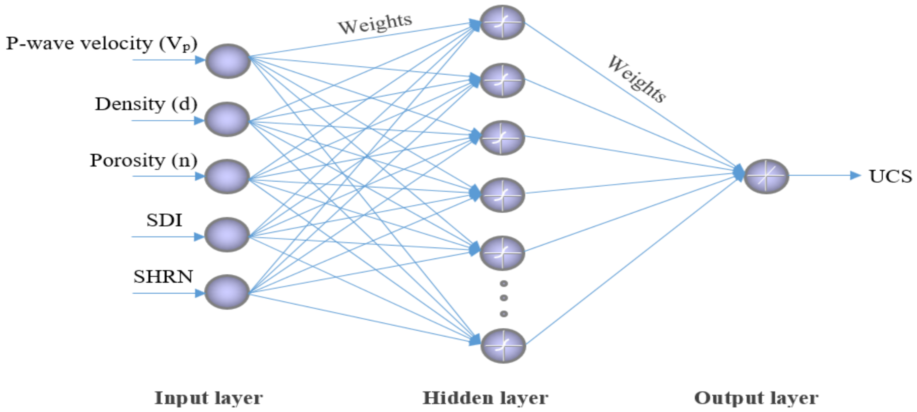

Fig 4.1: ANN model for UCS prediction

Two neural network structures were implemented in the MATLAB software environment to predict UCS, and E. Back-propagation training algorithm was utilized in the two feed-forward networks trained using the Levenberg Marquardt algorithm. The transfer functioned called the hyperbolic tangent sigmoid transfer function is used in the hidden layer, and a pure line transfer function is used in the output layer (for both UCS & E models). For each of the ANN models developed, the researchers used a manual trial and error approach to find the number of neurons in the hidden layer. As in each stage of analyses, the numbers of neurons were increased in search of the optimum model. Since the weights were randomly valued, the learning process can be trapped in a local minimum. Hence, each developed network has been trained many times, and the most competent model was selected. The training process stops when the sum of mean squared error is minimized or falls within an acceptable range.

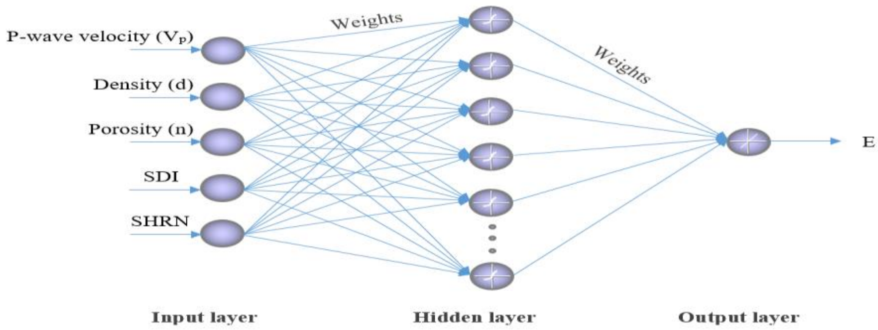

Fig 4.2: ANN model for E prediction

Both developed models have a three-layer feed-forward network that consists of an input layer (5 neurons), one hidden layer (25 neurons for the model I and 15 neurons for model II), and one output layer (1 neuron) (Fig. 4.1 & 4.2)

5. RESULTS AND DISCUSSIONS

5.1 Prediction of UCS & E by Linear and Non-linear MVRA

Empirical equation 4.1, 4.2, 4.3, 4.4 by linear and non-linear MVRA are used to estimate UCS & E from their respective input data. The estimated UCS & E values are plotted with measured UCS & E values in Figure 5.1, 5.2,5.3, 5.4, which are used to compare the measured UCS & E respectively with estimated UCS & E from inputs of P-wave velocity, density, porosity, Schmidt hammer rebound number, slake durability index, respectively. The figures show that the data and empirical model used provided a satisfactory estimation of UCS & E values. Based on the visual judgement of the performance of the empirical models, the estimated UCS & E from equations 4.1, 4.2, 4.3, 4.4 seems to be close to the measured one but not all estimated UCS & E values are relative to the measured ones, but they have the same trend.

5.2 Prediction of UCS & E by Artificial Neural Networks

ANN model-1 & 2 are used to estimate UCS & E from their respective input datasets. The correlation between predicted and the observed value of UCS & E are displayed in Figure 5.5 & 5.6, which are used to compare the measured UCS & E with estimated UCS & E respectively from inputs of P-wave velocity, density, porosity, Schmidt hammer rebound number, slake durability index, respectively. From the figures, it seems that the data and ANN model used has provided a highly satisfactory estimation of UCS & E values. Based on the visual judgement of the performance of the ANN models, the estimated UCS & E values seems to be closer than the MVRA models to the measured data values.

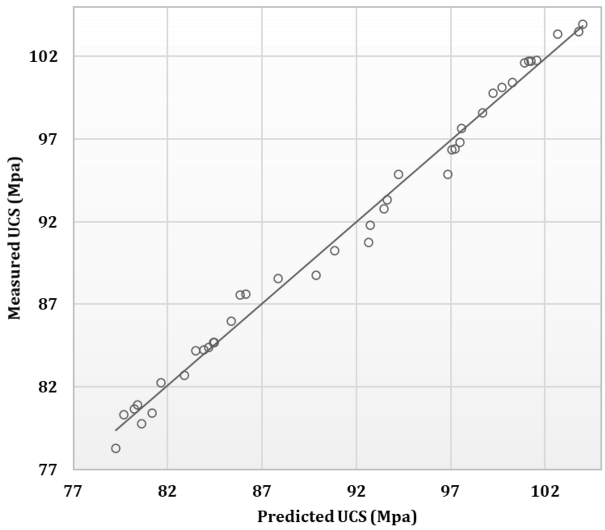

Fig 5.1: Relationship between measured and predicted UCS by linear MVRA

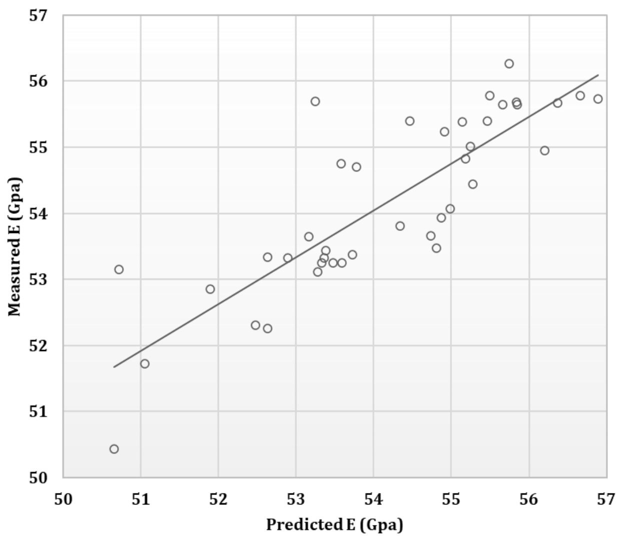

Fig 5.2: Relationship between measured and predicted E by linear MVRA

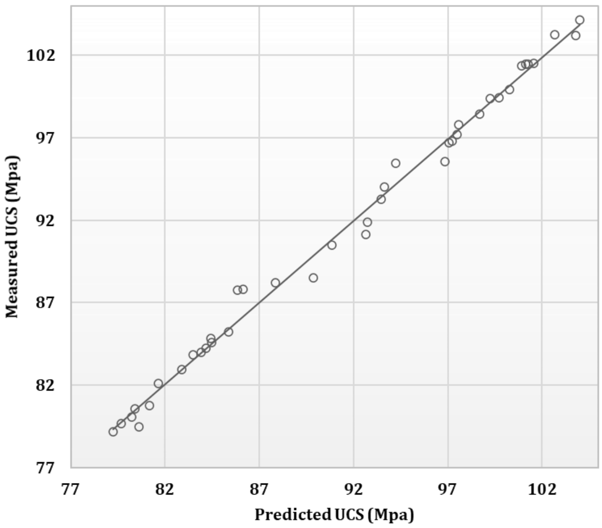

Fig 5.3: Relationship between measured and predicted UCS by non-linear MVRA

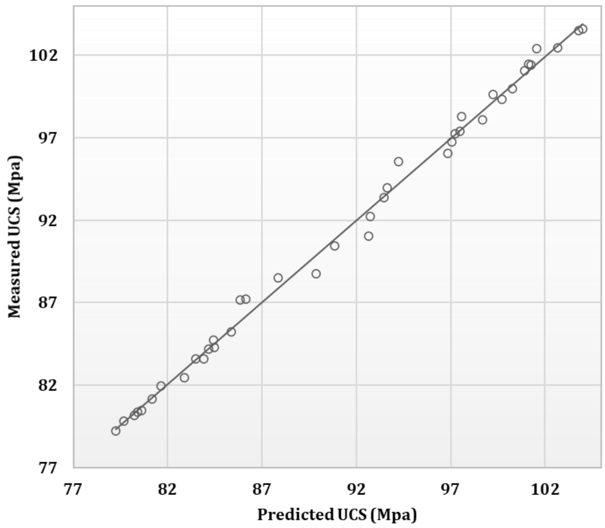

Fig 5.5: Relationship between measured and predicted UCS by ANN

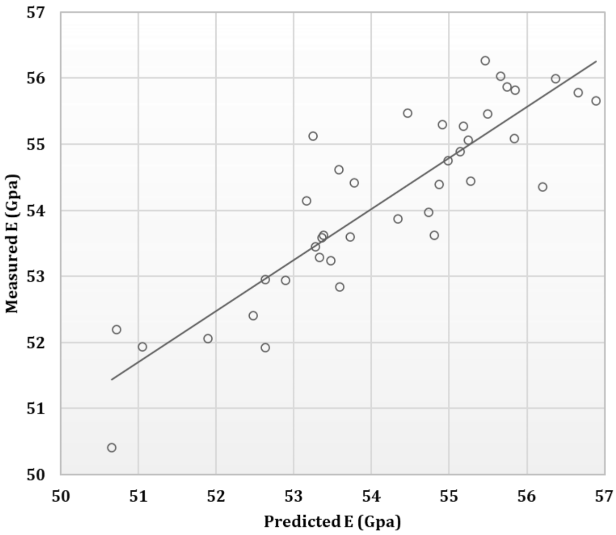

Fig 5.4: Relationship between measured and predicted E by non-linear MVRA

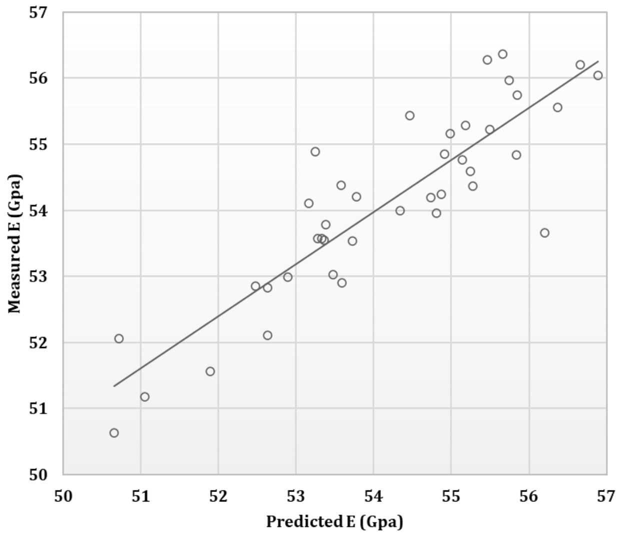

Fig 5.6: Relationship between measured and predicted E by ANN

Table 4.2: Descriptive statistics of non-linear MVRA for UCS and E

Parameter	Model	R^2	RMSE	AIC	VAF	AAREP
UCS	Linear MVRA model	0.850	0.740	-6.353	85.018	71.976
E	Linear MVRA model	0.709	0.916	-1.556	70.856	117.110
UCS	Non-linear MVRA model	0.910	0.745	-5.145	91.288	53.236
E	Non-linear MVRA model	0.774	0.831	0.580	77.422	104.340
UCS	ANN model-1	0.980	0.729	-10.628	98.792	44.792
E	ANN model-2	0.866	0.766	-1.567	85.966	104.170

5.2 Prediction of UCS & E by Artificial Neural Networks

statistical techniques were applied to estimate the UCS and E from the results of laboratory tests using empirical models to distinguish between the estimated UCS and E values with the lab oratorically measured UCS and E values reported for the same sample data from the study area. The trend and statistical outcomes of estimated Uniaxial compressive strength and modulus of elasticity are compared with measured UCS and E. Then, five statistical performance indicators are used in the study to assess the empirical equations upon their reliability and prediction performance. In addition to the Coefficient of determination (R^2), the Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), Variance Accounted For (VAF), and Absolute Average Relative Error Percentage (AAREP) are used to assess the UCS and E prediction. The coefficient of determination (R^2) can be calculated as

$$R^2 = \frac{\sum_{i=1}^{N}(y)^2 - \sum_{i=1}^{N}(y-y')^2}{\sum_{i=1}^{N}(y)^2} \quad (5.1)$$

N is the number of rock sample data used in the analysis; y and y' are measured and predicted values, respectively. If the coefficient of determination is nearly or equal to 1, the model will be excellent.

RMSE estimates the variation of predicted UCS & E values from the measured UCS & E values. RMSE is calculated as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y-y')^2}{N}} \quad (5.2)$$

Whereas N is the number of rock sample data used in the analysis, y and y' are measured and predicted values, respectively. Its value will always be non-negative, and a value of zero indicates a perfect fitness of a model to the data. In general, a low RMSE value shows a high forecasting ability of empirical equation or model and input data.

Akaike Information Criterion (AIC) is also estimated to compare the forecasting models' performance in the study. The AIC is calculated as

$$AIC = N \ln\left(\sum_{i=1}^{N}\frac{(y-y')^2}{N}\right) + 2\,n_p \quad (5.3)$$

Where N is the number of rock data used in the analysis, y and y' is measured and predicted values, respectively, np is the number of parameters that are need to be predicted. The model will be highly effective when AIC has the minimum value.

Variance Accounted For (VAF) measures the preciseness of prediction methods. The VAF can be calculated as follows

$$VAF = \left(1 - \frac{Var(y-y')}{Var(y)}\right) \times 100\ \% \quad (5.4)$$

Var is the variance, y and y' are measured, and predicted values, respectively High VAF denotes high prediction performance.

Absolute Average Relative Error Percentage (AAREP) measures the prediction accuracy of the estimation method. AAREP is calculated as

$$AAREP = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y-y\prime}{y}\right| \times 100\ \% \quad (5.5)$$

N is the number of rock sample data used in the analysis; y and y' are measured and predicted values, respectively. The smaller the value of AAREP, the more reliable the estimation.

The calculated indices from the equations 5.1, 5.2, 5.3, 5.4, 5.5 are tabulated in Table 5.5

6. CONCLUSION

The main objective of this study is to determine a rock's mechanical strength parameters using data sets for quick, easy application and low-cost estimation at the preliminary stage of site investigation. In this research, the artificial neural networks were used to predict UCS and E of limestone rocks and compared with linear and non-linear multivariate statistical models along with experimental data set. Geological conditions of the study area were studied, and limestone rock samples were collected from the study area for research, and laboratory analyses were carried out to determine 40 data sets of geotechnical properties. Each of the data sets comprises density (d), p-wave velocity (V_p), slake durability index (SDI), porosity (n), uniaxial compressive strength (UCS), Schmidt hammer rebound value (SHRN), modulus of elasticity (E). Initially, linear multivariate regression analyses were implemented to establish the correlations between UCS, E and V_p, d, n, SHRN, SDI, and non-linear multivariate regression analyses and ANN application with five inputs and one output. Four equations were suggested by using weight values determined by using linear and non-linear MVRA to predict UCS and E of the limestone rocks. The statistical performance analysis techniques like Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), Variance Accounted For (VAF), and Absolute Average Relative Error Percentage (AAREP) indices for the models predicting the UCS and E were determined. From the obtained results of linear (for UCS, R^2=0.850; for E, R^2=0.709) and non-linear (for UCS, R^2=0.910; for E, R^2=0.774) multivariate regression analyses, there are statistically satisfactory relationships between uniaxial compressive strength and modulus of elasticity with p-wave velocity, density, porosity, Schmidt hammer rebound value, slake durability index. Upon correlations, it is found that the p-wave velocity has a significant degree of dependence than other input variables to predict UCS & E. The R^2 value (UCS=0.980, E=0.866) of the ANN model is exhibiting its higher prediction performance over linear and non-linear MRVA models. On comparisons of performance indices, ANN has demonstrated higher R^2, higher VAF, lower value of RMSE & AIC, and minimum value of AAREP than linear and non-linear multivariate regression analyses both UCS and E. The high performance of the artificial neural network model was obtained from the greater degree of robustness and fault sensitivity than traditional linear and nonlinear MVRA statistical models as there are many more processing neurons, and each has a primary local connection. It is shown that the constructed ANN model exhibits high and reliable performance in predicting E and UCS of the limestone rocks. The performance comparison also showed that a neural network is a good approach for minimizing the uncertainties in predicting rock parameters. However, it should be noted that the prediction equations derived are valid only for understudied limestone rocks with similar characteristics.

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BIOGRAPHIES

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