A Simulation Approach to Predict Uniaxial Compressive Strength of Shale and Sandstone Samples Using Artificial Neural Network

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Abstract

Proper determination of Unconfined Compressive Strength (UCS) of rocks is a crucial subject in design of geotechnical structures. Although direct determination of UCS through laboratory test appears to be relatively simple, obtaining proper core segments specifically for weathered rocks is difficult and expensive. It is well established that UCS can be estimated indirectly using rock index properties. In comparison to the direct test, indirect prediction of UCS is relatively easier and cheaper. This study involves extensive laboratory tests on 32 datasets of shale and sandstone in various weathering grades obtained from excavation site in Johor, Malaysia. The laboratory tests include UCS test, Brazilian Tensile Strength (BTS) test, Point Load Index Test (Is(50)), P-wave velocity (Vp) test Schmidt Hammer Rebound Number (Rn) and Dry Density (DD) measurement. The application of Artificial Neural Network (ANN) in UCS prediction is highlighted in this study. For this reason, BTS, Is(50), Vp, Rn and DD were considered as input parameters while the UCS was set to be the output. The ANN results shows the superiority of ANN in UCS prediction.

Keywords: Unconfined Compressive Strength UCS, Laboratory Tests, Artificial Neural Network.

1. INTRODUCTION

In analysis of geotechnical problems such as dam and tunnel design, drilling and mechanical rock excavation, determination of Unconfined Compressive Strength (UCS) of the rocks can be considered as a great factor (Bieniawski 1974). The UCS of the rock is determined directly by testing the behavior of the rock specimens under axial load in the laboratory. The UCS test is standardized by American Society for Testing and Materials (ASTM) and International Society for Rock Mechanics (ISRM). However, direct determining of UCS may have some kinds of constraints in the laboratory. Having access to sufficient number of high quality cores specifically when rocks are highly fractured, weak and weathered, is extremely difficult. Besides, direct method of UCS test is destructive, time consuming and expensive (Gokceoglu and Zorlu 2004).

An ANN is a form of analysis which is based on simulation of the human nervous system. One of the major advantages of ANN is its efficient handling of highly non-linear relationships in data, even when the exact nature of such relationship is unknown. Therefore, neural networks are well suited for UCS prediction, because of the complex nature of interrelationships among the various quality parameters, composition and processing conditions. In the present paper, an attempt has been made to predict UCS of shale and sandstone samples obtained from excavation site in Johor, Malaysia using ANN technique.

2. BACKGROUND

Numerous researchers worked on the prediction of UCS using soft computing methods. The possibility for implementation of both neural network and statistical models for prediction the UCS and other strength properties of schistose rock from the petrographic properties were investigated in a study by Singh et al.
In their study the strength properties were estimated from mineral composition, grain size, aspect ratio, form factor, area weighting, and orientation of foliation planes of weakness. They have used 112 data sets for training a back propagation neural network. According to their findings ANN prediction model is more accurate than conventional statistical techniques. Gokceoglu and Zorlu (2004) used both fuzzy model and regression techniques to predict UCS and Young’s modulus (E) of problematic rocks. Point load index, block punch index, P-wave velocity, and tensile strength of 82 samples were considered as input layers to predict UCS and E in their study. They concluded that fuzzy model revealed the most reliable predictions when compared with the simple and multiple regression models. Gokceoglu and Zorlu (2004) used both fuzzy model and regression techniques to predict UCS and Young’s modulus (E) of problematic rocks. Point load index, block punch index, P-wave velocity, and tensile strength of 82 samples were considered as input layers to predict UCS and E in their study. They concluded that fuzzy model revealed the most reliable predictions when compared with the simple and multiple regression models. Dehghan et al (2010) used feed forward neural network, and regression analysis to predict UCS and E. In their study, some rock index parameters such as P-wave velocity, point load index; Schmidt hammer rebound number and porosity were considered as inputs layers to predict UCS and E of 30 dataset of Travertine rock samples. They concluded that the results of predictions made by ANN method seemed to be more reliable than those performed by other methods. Monjezi et al. (2012) used predictive models based on hybrid neuro-genetic approach and multivariable regression analysis to predict the UCS of 93 samples on different rock types including sandstone, limestone, dolomite, a few of them are mentioned. In their study, density, porosity, and Schmidt rebound number were considered as input parameters. According to their conclusion it was observed that accuracy of the hybrid neuro-genetic model is significantly better than regression model. Rabbani et al. (2012) conducted a study for determination of UCS based on ANN. In their study, porosity, bulk density, and water saturation of different rock samples were considered as input layers while UCS was considered as output. They demonstrated the applicability and feasibility of ANN to predict the UCS.

3. **CASE STUDY AND DATA COLLECTION**

This paper is based on case study of excavation site on weathered sedimentary rocks. The site is located at Nusajaya, Johor, Malaysia. The view of mentioned site is shown in Figure 1. The Nusajaya site is mainly composed of shale and sandstone layers with thickness vary from few centimeters to 2 meters. The sandstones are massive and inter bedded with shale layers. Rock hardness varies considerably at Nusajaya mainly due to type of the rock and weathering grades. The upper layer is more weathered in comparison to the bottom layer. Some rocks such as shale can be excavated without ripping, whereas others may need ripping or blasting. Nevertheless, the Nusajaya site is characterized mainly by its subdued topography. The bedding strikes almost in the north-northwest direction with dipping of 15° - 80° whereas the ridge of the site is composed mainly of argillaceous rocks and has been subjected to considerable dissection.

![Figure 1. View of the excavation site at Nusajaya, Johor](image)

In order to obtain sufficient rock samples, an extensive field study was conducted to select rock blocks suitable for standard core preparation machine. Even though approximately 100 blocks were collected from the field, only 32 good quality sample sets were obtained for rock characterization. A total number of 192 (32 datasets) laboratory tests include BTS, Is(50), Vp, Rn, DD, and UCS were conducted. When applying the
tests, the procedure suggested by ISRM (1985) for the point load index tests and ISRM (1981) for the other tests were considered.

4. **ARTIFICIAL NEURAL NETWORK**

Artificial Neural Networks (ANNs) are interconnected groups based on the operation of biological neural networks and emulation of biological neural system that uses a mathematical or computational model for data processing. In contrast to the most statistical and empirical methods, which need previous knowledge about the nature and relationships among the data, ANNs use of data examples to learn and obtain the suitable relationship among the data. The first neural network model was introduced by McCulloch and Pitts (1943). They combined many simple processing units together that could lead to an overall increase in computational power. The concept of Perceptron was introduced by Rosenblatt (1958) that can be seen as the simplest kind of feedforward neural network. The research on ANNs decreased between 1970 and 1985 because the Perceptron could not learn certain important functions. A solution to the problem with multi-layer networks was backpropagation network. This network back propagated the error encountered at the output layer to the hidden layer so that the changes in weights could be calculated. This type of network has successfully been used in many applications. In any event, ANNs were later developed by many researchers who described the structure and operation of ANNs (e.g., Rumelhart et al. 1986; Hopfield and Tank, 1986). ANN design includes the definition of several parameters; input and output parameters, transfer function, number of hidden layer(s), and number of nodes in hidden layer(s).

5. **UCS PREDICTION USING ANN**

In order to utilize the ANN method to predict UCS, two different sedimentary rocks were investigated. To train and verify the ability and accuracy of the ANN method to predict UCS, 32 datasets of laboratory tests include BTS, Is(50), Vp, Rn, and DD were conducted. The range of the various input and output parameters considered for developing neural network are shown in Table 1.

**Table 1. Input and output quantities used in model**

<table>
<thead>
<tr>
<th>Variable Category</th>
<th>Variables</th>
<th>Unit</th>
<th>Symbol</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>Brazilian Tensile Strength</td>
<td>(MPa)</td>
<td>BTS</td>
<td>1.6</td>
<td>4.4</td>
</tr>
<tr>
<td>Input</td>
<td>Point Load Index Test</td>
<td>(MPa)</td>
<td>Is(50)</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Input</td>
<td>P-wave velocity</td>
<td>(m/s)</td>
<td>Vp</td>
<td>2045</td>
<td>2994</td>
</tr>
<tr>
<td>Input</td>
<td>Schmidt Hammer Rebound Number</td>
<td>(MPa)</td>
<td>Rn</td>
<td>19</td>
<td>92</td>
</tr>
<tr>
<td>Input</td>
<td>Dry Density</td>
<td>(kg/m³)</td>
<td>DD</td>
<td>2110</td>
<td>2947</td>
</tr>
<tr>
<td>Output</td>
<td>Unconfined Compressive Strength</td>
<td>(MPa)</td>
<td>UCS</td>
<td>16</td>
<td>88</td>
</tr>
</tbody>
</table>

6. **EXCAVATE IN LIFTS**

A MATLAB code was prepared for prediction UCS using feed forward ANN. The input layer consists of five parameters including BTS, Is(50), Vp, Rn and DD were used to estimate UCS. In order to obtain superior performance of ANN to predict UCS, the optimal architecture including the number of hidden layer(s) and the number of nodes in the hidden layer(s) was determined using the trial and error method. Therefore, 12 models were trained and tested with different architectures to determine the optimal architecture. Numbers of training epochs were set 1000 for all models. Based on the values of MSE and correlation coefficient, R, the network that produced the best agreement with the actual data was selected. Table 2 shows the architecture of proposed models.
Table 2. Architecture of proposed models

<table>
<thead>
<tr>
<th>Model number</th>
<th>Hidden layers</th>
<th>Number of nodes in hidden layers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
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<tr>
<td>3</td>
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<td>15</td>
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<tr>
<td>12</td>
<td>2</td>
<td>30</td>
</tr>
</tbody>
</table>

To evaluate the performance of the proposed models and select an appropriate model, values of R and MSE were investigated for comparing the performance of models. According to Figures 2 and 3 model number 2, consisted of one hidden layer with 10 nodes produced the highest correlation and lowest MSE among the models. Accordingly, this model was selected to predict UCS. For this model the R values were obtained as 0.98 and 0.94 for training and testing datasets, respectively. The obtained MSR for the mentioned model are 0.008 and 0.078 for training and testing, respectively. Architecture of the optimum model is shown in Figure 4.

Figure 2. Correlation coefficient for proposed models
7. RESULT AND DISCUSSION

Figures 5 and 6 illustrate the performance of the selected ANN model for training and testing datasets, respectively. These figures show that how well the variation in the output of the networks is explained by the actual UCS. If the R is equal to 1, then there is perfect correlation between actual values and output of the networks. Figure 7 shows the concordance between actual and predicted values for testing datasets obtained by the selected model. The results indicate that the proposed model is capable for UCS prediction with high degree of accuracy.
Figure 5. Performance of the proposed model using training dataset

Figure 6. Performance of the proposed model using testing datasets
In order to have a better understanding of the prediction power of ANN, the predicted UCS through ANN for all 32 datasets are plotted against their determined values in the laboratory in Figure 8. As shown schematically in this Figure, the predicted UCS is really close to the actual UCS which shows the accuracy of ANN technique.

Figure 7. Concordance between the actual and predicted UCS for testing datasets

Figure 8. Comparison between Measured UCS and Predicted UCS by ANN
8. CONCLUSION

In order to predict UCS, a number of 192 laboratory tests were conducted on 32 shale and sandstone sample sets. The core samples in various grades were taken from Nusajaya excavation site in Johor, Malaysia. ANN technique was implemented for UCS prediction. BD, Is(50), Rn, BTS, and Vp were considered as input parameters to predict UCS. In order to determine an optimum model, a series of analyses were conducted to determine the optimum architecture of ANN by means of trial and error method. It is found that the ANN predictive model with one hidden layer and 10 nodes can estimate the UCS much better than other models. For this model the R values were obtained as 0.98 and 0.94 for training and testing datasets, respectively which show the accuracy of ANN technique. In addition, in order to have better UCS prediction in further works, care must be taken regarding the ranges of the laboratory results considered in this study.

7. REFERENCES