APPLICATION OF ARTIFICIAL NEURAL NETWORK (ANN) IN THE DETERMINATION OF THE DRILLABILITY INDEX (DI) OF A ROCK MASS

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Abstract

Artificial Neural Networks (ANN) have been applied to many interesting problems in different areas of science, medicine and engineering and in some cases, they provide state-of-the-art solutions. This paper investigates the application of an ANN model in mining to predict the Drillability Index (DI) of a rock mass given rock parameters such as uniaxial compressive strength, shear strength, tensile strength, abrasion and hardness. Drillability indicates whether penetration is easy or hard while penetration rate indicates whether it is fast or slow. Therefore, prediction of the drillability and penetration rate is very important in rock drilling. Penetration rate is a necessary value for the cost estimation and the planning of the drilling project. According to results of this study, Uniaxial Compressive Strength (UCS) rating has the highest weight of 0.051083 among the three parameters studied which reconfirms the literature review finding which indicates that UCS is the most important parameter in predicting drillability.

***Keywords**: Artificial Neural Networks, Drillability Index, Artificial Intelligence, Penetration Rate.*

INTRODUCTION

Neural networks are powerful forecasting tools that draw on the most recent developments in artificial intelligence research. They are non-linear models that can be trained to map past and future values of time series data and thereby extract hidden structures and relationships that govern the data. Neural networks are applied in many fields such as computer science, engineering, medical and criminal diagnostics, biological investigation, and economic research. They can be used for analysing relations among economic and financial phenomena, forecasting, data filtration, generating time-series, and optimization (Hawley, Johnson, and Raina, 1990; White, 1988; White 1996; Terna, 1997; Cogger, Koch and Lander. 1997; Cheh, Weinberg, and Yook, 1999; Cooper, 1999; Hu and Tsoukalas, 1999; Moshiri, Cameron, and Scuse, 1999; Shtub and Versano, 1999; Garcia and Gencay, 2000; and Hamm and Brorsen, 2000).

An artificial neural network is a mathematical model or computational model based on biological neural networks, in other words it is an emulation of a biological neural system (Figure 1). It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase.

ARTIFICIAL NEURAL NETWORK STRUCTURE

The model of the artificial neuron or processing element (PE) forms the basis of the ANN structure (Figures 2 and 3).

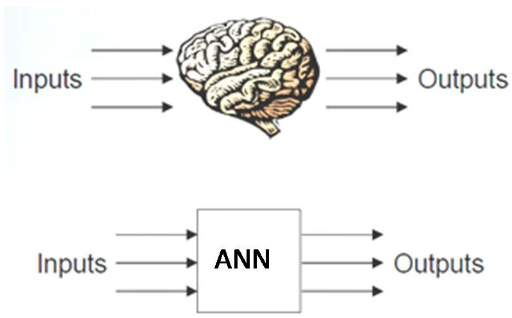

Figure 1: Structure of biological and artificial neural network systems

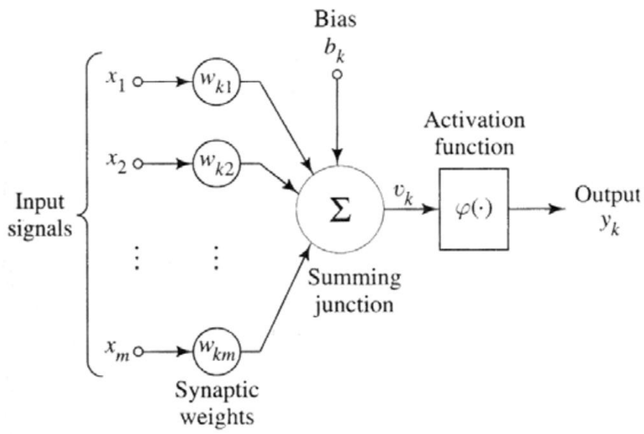

Figure 2: Artificial neuron structure or Processing Element (Haykin, 1999)

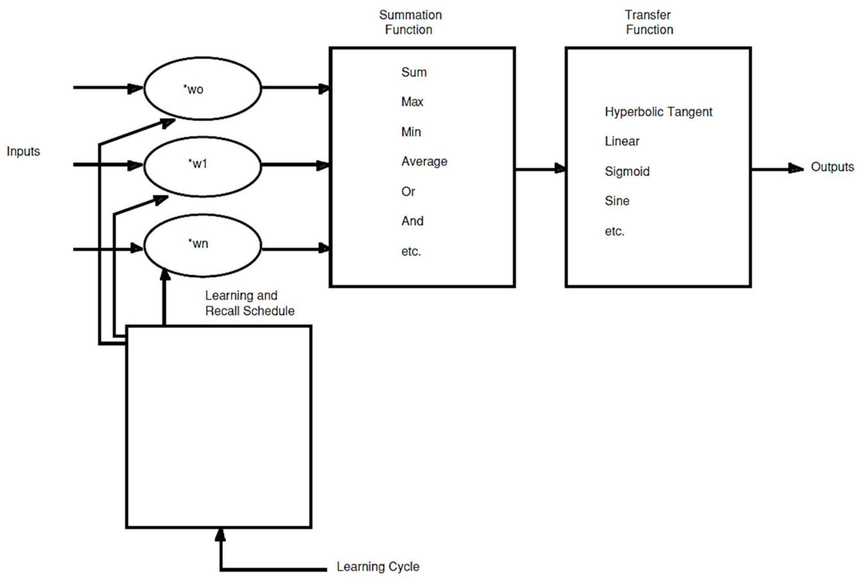

Figure 3: A Model of a “Processing Element” (DACS, 1992)

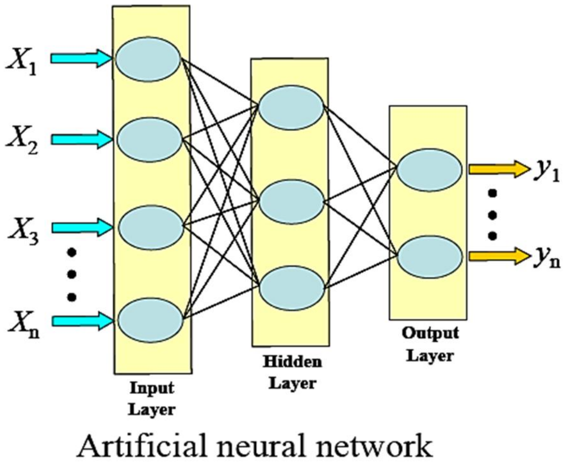

Figure 4: Typical structure and operation of ANNs (Shahin, Jaksa & Maier, 2008)

This layered structure is the most common in ANNs and is usually called the fully connected feed forward or a cyclic network. However, there are ANNs that do not adopt this structure. The starting point of the ANN structure is a layer of input units that allows the entering of information into the network (Figure 4). The input units cannot be considered as PEs mainly because there is no processing of information taking place at them with the exception of normalisation (when required). Normalisation ensures that changes in the signals of different inputs have the same effect on the network's behaviour regardless of their magnitude.

The Backpropagation Algorithm

The backpropagation algorithm is used in layered feed-forward ANNs (Rumelhart and McClelland, 1986). This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The backpropagation algorithm uses supervised learning, which means that an algorithm is provided with examples of the inputs and outputs one wants the network to compute and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

Connection / Synaptic weights

The signals are multiplied by a weight which is different for every connection. Connection weights have the function of amplifying, attenuating or changing the sign of the input signal. The scalar weights determine the strength of the connections between interconnected neurons. A zero weight represents the absence of a connection and a negative weight represents an inhibitory relationship between nodes. In general, the output of node **i** is multiplied by the weight of the connection between node **i** and **j** to produce the input signal to node **j** ($\mathbf{X_i W_{ji}}$). Hence connection weights represent the strength of the connection between two nodes.

Following the input layer is one or more internal or hidden layers (see Figure 4). The use of the word hidden is mainly due to the fact that they are not accessible from outside the ANN. The first hidden layer is fully interconnected with the units of the input layer. In other words, all Processing Elements of the hidden layer receive the signal from each input unit. In the case of more than one hidden layers, there will be full interconnection between subsequent layers as in the case of the input and first hidden layer. Each processing element in a specific layer is fully or partially connected to many other processing elements via weighted connections. From many other processing elements, an individual processing element receives its weighted inputs, which are summed and a bias unit or threshold is added or subtracted (Equation 1).

$$Y = \sum_{i=1}^{n} X_i W_{ji} + b_k \qquad (1)$$

where:

b_k is the bias.

The bias unit is used to scale the input to a useful range to improve the convergence properties of the neural network.

Transfer functions

Transfer functions are mathematical formulae that give the output of a processing element as a function of its input signal. Transfer functions can take a variety of forms:

(i). Threshold function;
(ii). Hard limiters; and
(iii). Continuous function;

The result of this combined summation is passed through a transfer function (e.g. logistic sigmoid or hyperbolic tangent) to produce the output of the processing element (Equations 2 and 3).

Hyperbolic tangent $f(x) = \tanh x$

$$= 1 - \frac{2}{1+\exp(2x)} \qquad (2)$$

Logistic $f(x) = \frac{1}{1+\exp(-x)}$ (3)

Formation of training, testing and validation sets

The data set is divided into three distinct sets called training, testing and validation sets. The training set is the largest set and is used by the neural network to learn patterns present in the data. The testing set is used to evaluate the generalisation ability of a supposedly trained network. A final check on performance of the trained network is made using a validation set.

Learning

Learning is the process in which the weights are adjusted in response to training data provided at the input layer and, depending on the learning rule, at the output layer. The learning process allows a network to adapt its response with time in order to produce desired output. Learning methods in neutral network can be broadly classified into five types;

(i). Supervised learning;
(ii). Unsupervised leaning;
(iii). Graded learning;
(iv). Hybrid learning; and
(v). Non-adaptive learning.

In this study, supervised learning will be used adjusting the weights. This type of learning is represented in Figure 5.

ANN MODEL FOR DRILLABILITY INDEX (DI) DETERMINATION

The basic architecture of the ANN for determining the drillability Index consists of three types of neuron layers i.e., five input parameters, one hidden layer and one output layer (the drillability index).

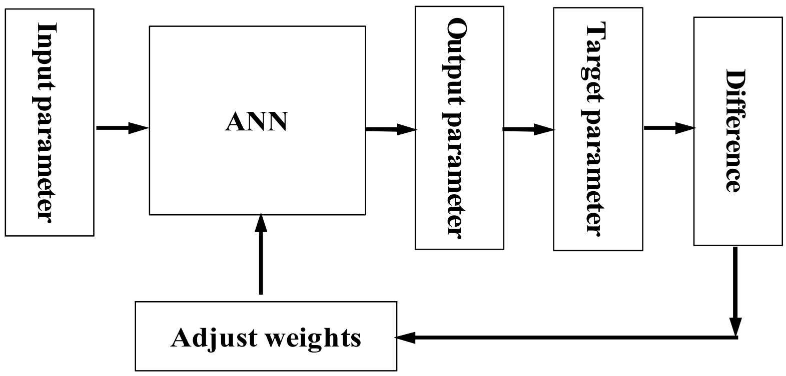

Figure 5: Typical learning cycle in the ANN Model

According to Kapageridis, 2002, the use of the word hidden is mainly due to the fact that they are not accessible from outside the ANN. The first hidden layer is fully interconnected with the units of the input layer. In other words, all PEs of the hidden layer receive the signal from each input unit. The signals are multiplied by a weight which is different for every connection.

Parameters of rock mass drillability classification

Drilling and blasting play vital roles in both opencast and underground mining. These operations do not only affect the cost of production directly but as well the overall operational costs (Busuyi, 2009). The penetration rate and economics of the holes opened during the development and production activities in underground and open-pit mines play crucial roles. Therefore, prediction of the penetration rate is very important in rock drilling. The penetration rate is a necessary value for the cost estimation and the planning of the project. Drillability and penetration rate can be defined as similar terms. While drillability indicates whether penetration is easy or hard, penetration rate indicates whether it is fast or slow.

Rock drilling is performed with a number of techniques ranging from rotary/percussive drilling in very hard rock, via rotary/crushing drilling in medium hard rock, down to cutting in soft rock types. Rock drilling mainly depends on operational variables and rock characteristics. Operational variables are known as controllable parameters: rotational speed, thrust, blow frequency and flushing. However, rock properties and geological conditions are uncontrollable parameters (McGregor, 1967; Beste, *et al.*, 2007). The hardness of the rock, rock strength (i.e., uniaxial compressive strength, shear strength, tensile strength, etc.) and abrasion are the most important unchangeable factors. Taking into consideration the optimum penetration rate, choosing the correct drilling machine, the petrographic structure of the rock, its hardness, abrasion, physical characteristics and mechanical properties are to be determined firstly by in-situ and laboratory studies. Therefore, the performance of drilling is dependent on technical characteristics of the drilling, drillability of rock and work organization.

Determination of model inputs

There are 5 input parameters, affecting rock drillability as below:

(i). Uniaxial Compressive Strength (UCS);
(ii). Shear strength;
(iii). Tensile strength;
(iv). Abrasion; and

(v). Hardness.

These parameters can be subdivided into four categories, which are rock physical properties, rock mechanical properties, rock mass parameters, and the indexes developed by researchers. The most widely accepted parameters among each category are listed below.

(i). Rock Mechanical Characteristics: UCS and tensile strength
(ii). Rock Physical Properties: Density and Porosity;
(iii). Rock Mass Parameters: P-wave velocity and discontinuity frequency; and
(iv). Some indexes to express rock properties regarding drillability such as: Specific Energy and Drilling Rate Index.

The most widely used rock mechanical parameter is UCS, which has been reported in 25 papers reviewed as part of this research. Among rock physical properties, density was the most adopted parameter. Moreover, in aspect of rock mass parameters, P-wave velocity is the most recognized one. Therefore, a rock drillability characterization system was developed to incorporate UCS, density and P-wave velocity, representing rock mechanical characteristics, physical properties and rock mass parameters respectively, to estimate the drillability. The parameters and their respective symbols are provided in Table 1.

Data from an experimental study conducted by Howarth, *et al* (1986) was utilized to investigate the relationship between UCS and penetration rate. The relationship between penetration rates and UCS values is shown in Figure 6.

Table 1: Input and output parameters

Type of data	Name of parameter	Symbol	Unit
Inputs	Uniaxial compressive strength	X_1	MPa
	P-wave velocity	X_2	km/sec
	Density	X_3	kg/m^3
Output	Rock Drillability Characterization index (RDC index)	I	1

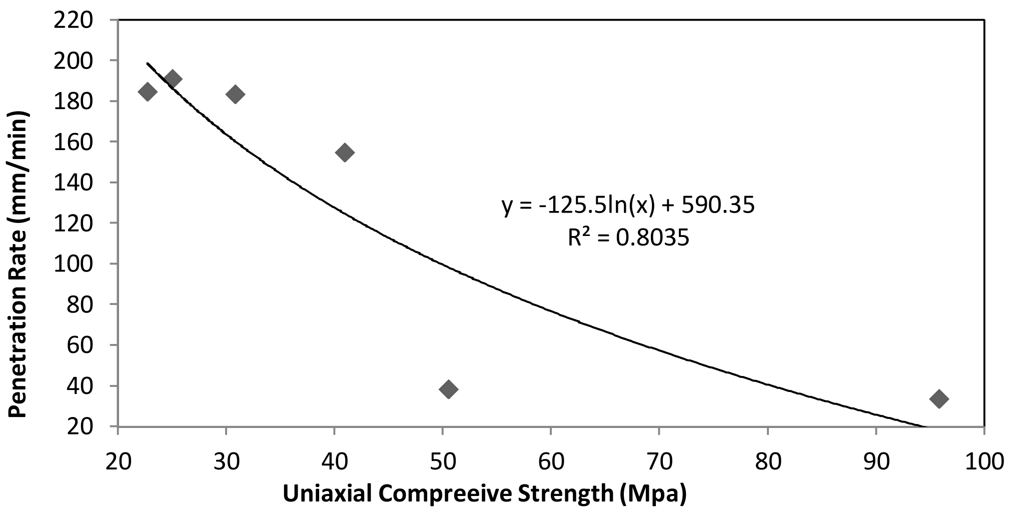

Figure 6: Relation between UCS and penetration rate

Uniaxial compressive strength (UCS) ranging from 20-100 MPa, is divided into four classes as shown in Table 2. Roughly a penetration rate is allocated to each class according to Figure 6.

Following the same procedure, data from the study conducted by Howarth, *et al* (1986) was also utilized to investigate the relationship between P-wave velocity, density and penetration rate. P-wave velocity ranging from 2 to 7 Km/sec is divided into four classes and shown in Table 3.

Density parameter ranging from 2 to 2.8 g/cm^3 is divided into 4 classes and is shown in Table 4.

Weight Analysis

A data set from the research conducted by Niyazi (2011) was used to calculate the weight for diamond drilling. Based on the rating system calculated before, the original data was then rated and tabulated in Table 5.

Table 2: Uniaxial compressive strength rating

UCS (MPa)	20 - 30	30 - 40	40 – 50	50 – 100
Penetration Rate (mm/min)	190	170	100	40

Table 3: Rating of P-wave velocity

P-wave Velocity (Km/sec)	2 – 3	3 – 4	4 – 5	5 - 7
Penetration Rate (mm/min)	230	135	80	5

Table 4: Density rating

Density (g/cm^3)	2 – 2.2	2.2 – 2.4	2.4 – 2.6	2.6 – 2.8
Penetration Rate (mm/min)	290	205	125	40

Table 5: Niyazi (2011) dataset rating

Rock type	**UCS**	**P-Wave**	**Density rating**	**Penetration**
Andsite	40	135	125	2.08
Afyon marble	40	5	40	9.97
Beige marble	40	5	40	2.69
Grey turf	170	230	290	18.53
Pink turf	190	230	290	31.91
Travertine	190	80	248	2.83
Travertine	190	135	290	25.07
Travertine	190	43	290	23.93

Based on the above input parameters, the computation mode of the rock mass drillability is given in Equation 4 as well as in Figure 5; Y is the output parameter of the ANN i.e. the rock mass drillability Index.

$$Y = \{X_1, X_2, X_3\} \tag{4}$$

where:

X_1: Uniaxial Compressive Strength (MPa);
X_2: P-wave velocity (km/s); and
X_3: Density (kg/m^3).

To approximate the weights in the model, directed random search is used. This method is based on random optimisation method of Matyas, 1965 and also includes refinements proposed by Solis and Wets, 1981. Unlike calculus based gradient descent methods, which move down the error surface in weight space, directed random search networks take random steps in weight space in an attempt to find the smallest error. A directed component is added to the random step so that previously successful directions are pursued.

The basic weight adjustment procedure to be followed was according to NeuralWare, Inc 1991 and is discussed below:

1. Weights in the network are assigned randomly;
2. A random step value is added to each weight;
3. The prediction error is calculated for each training sample;
4. (i) If the total error prediction is less than the previous best, the current weight values, which include the random step, become the new set of best weights;
   (ii) The current prediction error is stored as the new, "best" prediction error;
5. (i) If the total prediction error is greater than the previous best, the same random value is subtracted from each weight, producing a "reversal" step in the direction opposite to the previous random step;
   (ii) Steps 3 and 4 are repeated;
   (iii) If the reverse step fails to reduce the error, a completely different vector is added to the best weights and the process is repeated.

The ANN results of individual parameters are tabulated in Table 6. The coefficients of each parameter are used as the rating weights. As can be seen from this table, UCS rating has the highest weight among the three which reconfirms the literature review finding which indicates that UCS is the most important parameter in predicting drillability.

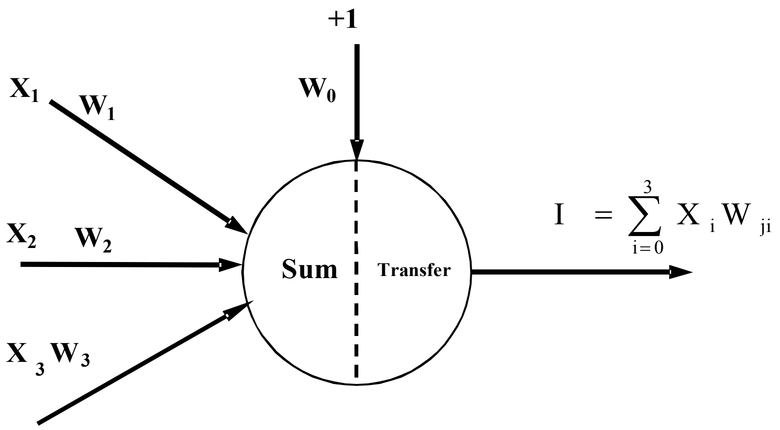

Figure 7: Operation of Processing Element for drillability Index determination

Table 6: Weight for individual parameters

Parameters	Weights
UCS Rating	0.051083
P-wave Velocity Rating	0.023351
Density Rating	0.027189

Network training and Testing

According to Yu, 2004 a neural network can be trained in two kinds of styles i.e., batch training and incremental training. In batch training, weights and biases of the network are only updated after all of the inputs are presented to the network, while in incremental (on-line) training the network parameters are updated each time an input is presented to it. After the training process, the performance of the trained network should be evaluated by applying unseen data to it and checking whether its outputs are still relevant to the targets. Here, the average error rate is used to measure the network performance.

CONCLUSION

According to previous research, the most influential factors of rock drilling, in terms of mechanical properties, physical parameters and mass condition of rocks, include uniaxial compressive strength, density and P-wave velocity. As a result, these three parameters were selected to develop a Rock Drillability Characterization index (RDC index) system. Neural networks have been proposed as useful tools in mining in a variety of applications. This paper has demonstrated that ANN can be applied to predict the drillability a rock mass. The ANN model will help in cost estimation and the planning of the project.

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