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Prediction of rock brittleness using nondestructive methods for hard rock tunneling

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ABSTRACT

The material and elastic properties of rocks are utilized for predicting and evaluating hard rock brittleness using artificial neural networks (ANN). Herein hard rock brittleness is defined using Yagiz' method. A predictive model is developed using a comprehensive database compiled from 30 years' worth of rock tests at the Earth Mechanics Institute (EMI), Colorado School of Mines. The model is sensitive to density, elastic properties, and P- and S-wave velocities. The results show that the model is a better predictor of rock brittleness than conventional destructive strength-test based models and multiple regression techniques. While the findings have direct implications on intact rock, the methodology can be extrapolated to rock mass problems in both tunneling and underground mining where rock brittleness is an important control.

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1. Introduction

The brittleness of rock is an important consideration in mechanical excavation and underground tunneling. Recent studies have cast doubt on the effectiveness of rock strength-based techniques (such as unconfined compressive strength or tensile strength) alone for characterizing intact rock brittleness. For example, Yagiz (2002, 2008, 2009) used the punch penetration test (Handewith, 1970; Dollinger et al., 1998; Szwedzicki, 1998; Dollinger and Raymer, 2002; Copur et al., 2003) to derive a brittleness index which was demonstrably superior to purely strength-based rock brittleness indices. Yagiz and Gokceoglu (2010) applied a fuzzy inference system and nonlinear regression model to predict rock brittleness. Further, Yagiz and Karahan (2015) applied various optimization techniques for estimating tunnel boring machine (TBM) performance using rock brittleness, as an input variable obtained from punch penetration test. Guo et al. (2012) used a non-strength based rock physics template to measure the variation of rock brittleness, mineralogy and porosity in shale. Tarasov and Potvin (2013) developed two rock brittleness criteria based on the balance between accumulated elastic energy and rupture/excess energy, which gave unambiguous characterizations of rock

brittleness under different loading conditions. It was Meng et al. (2015), however, who conducted perhaps the most comprehensive analysis and critique of commonly used brittleness indices. In addition to deriving their own brittleness (two) indices, Meng et al. (2015) concluded that strength-based brittleness indices typically ignore the influence of elastic strain and confining stress, which are required to characterize both the amount of accumulated energy during loading prior to failure, and the mechanism of energy consumption (brittle fracture, plastic deformation or fracture friction).

Obviously strength-based rock brittleness indices are still useful as indirect tools to assess material brittleness, given that rock strength and rock brittleness are not the same property. Indices utilizing the indirect Brazilian tensile, UCS (uniaxial compressive strength) (Hucka and Das, 1974; Altindag, 2002; Yagiz, 2006), and rock fragment size distribution (Blindheim and Bruland, 1998) have been very useful in evaluating mechanical excavation performance in tunneling. Using Bussinesq's pressure distribution concepts, Frank (1998) developed a rock cuttability index (RCI) by combining elastic constants (Poisson's ratio, Young's modulus) and strength parameters (UCS, tensile strength) useful for predicting excavation machinery performance from a small amount of representative intact rock core.

It is important, however, to systematically estimate rock brittleness under varying loading conditions and anisotropies, where strength-based techniques seem to fall short. There is generally a lack of adequate systems to characterize intrinsic material brittleness under the broad scope of absolute brittleness to ductility

Table 1
Global rock test database from the Colorado School of Mines used to build the ANN model.

Case	Rock type	Rock type code	Unit weight (kN/m^3)	P-wave velocity (m/s)	S-wave velocity (m/s)	Poisson's ratio, ν	Young's modulus, E (Pa)	Lame's constant	Brittleness index (kN/mm)
1	Igneous	[0 1 0]	25.9	3614	2386	0.11	3.0×10^{10}	4.0×10^{9}	27.2
2	Sedimentary	[0 0 1]	26.3	5561	3426	0.19	8.0×10^{10}	2.0×10^{10}	38.4
3	Sedimentary	[0 0 1]	26.5	4813	3067	0.16	6.0×10^{10}	1.0×10^{10}	27.4
4	Metamorphic	[1 0 0]	26.2	6577	3362	0.32	8.0×10^{10}	6.0×10^{10}	30.1
5	Sedimentary	[0 0 1]	26.6	6057	3607	0.23	9.0×10^{10}	3.0×10^{10}	19.6
6	Sedimentary	[0 0 1]	25.9	4530	2998	0.11	5.0×10^{10}	7.0×10^{9}	39.9
7	Sedimentary	[0 0 1]	25.8	4609	3031	0.12	5.0×10^{10}	8.0×10^{9}	39.9
8	Sedimentary	[0 0 1]	26.0	4829	3106	0.15	6.0×10^{10}	1.0×10^{10}	35.7
9	Sedimentary	[0 0 1]	24.8	4071	2727	0.09	4.0×10^{10}	4.0×10^{9}	35.7
10	Sedimentary	[0 0 1]	26.0	3953	2716	0.05	4.0×10^{10}	2.0×10^{9}	36.0
11	Sedimentary	[0 0 1]	26.0	4630	3025	0.13	5.0×10^{10}	8.0×10^{9}	36.0
12	Sedimentary	[0 0 1]	25.3	3972	2704	0.07	4.0×10^{10}	3.0×10^{9}	32.4
13	Sedimentary	[0 0 1]	25.3	3898	2661	0.06	4.0×10^{10}	3.0×10^{9}	32.4
14	Sedimentary	[0 0 1]	25.5	4453	2941	0.11	5.0×10^{10}	7.0×10^{9}	37.5
15	Sedimentary	[0 0 1]	25.8	4763	3004	0.17	6.0×10^{10}	1.0×10^{10}	35.6
16	Sedimentary	[0 0 1]	25.7	4424	2888	0.13	5.0×10^{10}	8.0×10^{9}	33.3
17	Sedimentary	[0 0 1]	25.7	4398	2876	0.13	5.0×10^{10}	7.0×10^{9}	35.4
18	Igneous	[0 1 0]	27.8	4981	3071	0.19	6.0×10^{10}	2.0×10^{10}	49.0
19	Igneous	[0 1 0]	26.5	4628	2869	0.19	5.0×10^{10}	1.0×10^{10}	63.8
20	Igneous	[0 1 0]	26.1	6194	3532	0.26	8.0×10^{10}	4.0×10^{10}	52.7
:	:	:	:	:	:	:	:	:	:
136	Sedimentary	[0 0 1]	26.0	4448	2958	0.10	5.0×10^{10}	6.0×10^{9}	25.4

Note: For the rock type code, the binary digits represent sedimentary [0 0 1], igneous [0 1 0] and metamorphic [1 0 0].

(Tarasov and Potvin, 2013). In addition, existing systems may sometimes contradict one another or be dependent on specific testing and measurement conditions, further restricting their use (Yagiz, 2009; Meng et al., 2015).

This study introduces a new approach to predict and evaluate rock brittleness using P- and S-wave velocities, elastic properties and rock type. In a non-destructive (i.e. non-invasive) fashion, the approach relates rock brittleness to rock type and elastic modulus. The method utilizes 30 years' worth of test data generated from rock samples collected around the world. To build the model, the data are processed using a neural network back propagation (BP) algorithm with Bayesian regularization. The results obtained using the new approach are compared to those available from commonly referenced standard techniques, and demonstrated to provide a better generalization and accuracy. In this paper, Yagiz (2002, 2009) method of quantifying brittleness is used in the model while recognizing that other equally suitable methods are also available. However, Yagiz (2002) brittleness index can be used as an input to predict TBM performance in hard rock. As a result Yagiz (2002, 2009) brittleness index is selected based on the availability of data, and not necessarily on superiority of performance to other brittleness indices.

2. Methodology

2.1. Global database

The database utilized consists of over 20,000 rock property test results and was compiled over a span of 30 years at the Earth Mechanics Institute (EMI), Colorado School of Mines. The EMI was founded in 1974 as a center for basic and applied research in rock mechanics and mechanical excavation. Since EMI's establishment, numerous rock tests have been conducted from tunneling and mining projects around the world, resulting in an extensive, comprehensive database for a wide variety of rock types. The data include conventional American Society for Testing and Materials (ASTM) standard rock strength test results such as point load strength, UCS, triaxial compressive strength, Brazilian tensile strength, P- and S-wave velocity tests, and specialized rock tests such as linear cutting, abrasivity, and punch penetration. After detailed assessment, suitable test parameters were selected from the global database to build the artificial neural networks (ANN) prediction model used in this study. The final model input parameters were rock type (igneous, metamorphic or sedimentary), unit weight, P-wave velocity, S-wave velocity, dynamic Poisson's ratio, dynamic Young's modulus, and Lame's constant. Representative final input parameters are shown in Table 1. Where P- and S-wave velocity data were unavailable, a preliminary neural net model was applied to provide the missing values based on existing P- and S-wave velocities, density and rock strength data.

2.2. Punch penetration test

The output parameter used in the neural network prediction is the brittleness index, obtainable from the punch penetration test — a key laboratory test conducted at EMI originally designed to measure the normal load on disc cutters (Handewith, 1970; Ozdemir and Wang, 1979; Yagiz, 2002; Rostami, 2008). In the punch penetration test, a standard conical indentor is pressed into a rock sample cast in a confining steel ring (Fig. 1). The load–displacement measurements of the indentor are then acquired with a computer system, and can be related to the mechanical
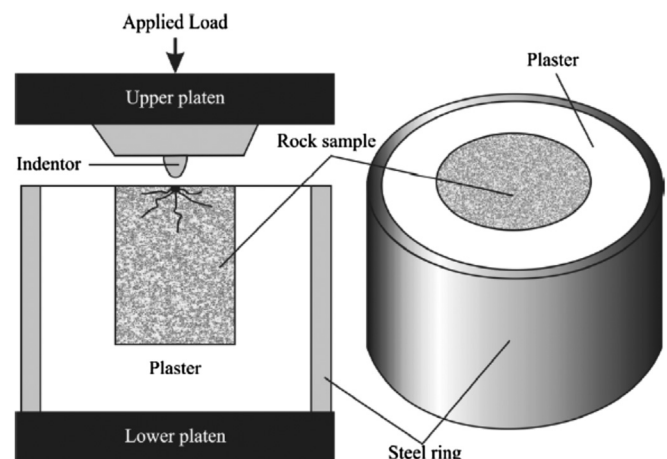

Fig. 1. Schematic of the punch penetration test (Yagiz, 2009).

cuttability (energy required for efficient chipping) of rock. Yagiz (2009) used the punch penetration test to develop a new approach of estimating rock brittleness with force−penetration curves (Fig. 2), which could be also related to standard compressive and tensile rock strengths:

$$BI = \frac{F_{\max}}{P_{\max}} \qquad (1)$$

$$BI_{\mathrm{P}} = 0.198\sigma_{\mathrm{c}} - 2.174\sigma_{\mathrm{t}} + 0.913\gamma - 3.807 \qquad (2)$$

where BI is the measured brittleness index in kN/mm, $F_{\max}$ is the maximum applied force on a rock sample in kN, $P_{\max}$ is the corresponding penetration at maximum force in mm, BI_{P} is the predicted brittleness in kN/mm, σ_{c} is the UCS in MPa, σ_{t} is the Brazilian tensile strength in MPa, and γ is the unit weight in kN/m^3.

2.3. ANN and back propagation

In this study, ANN modeling via BP was applied to developing the brittleness prediction model as discussed in Sections 3−5. The fundamentals of ANN modeling have been covered extensively (e.g. Bishop, 1995; Samarasinghe, 2006; Haykin, 2009). Artificial neurons (modeled after biological neurons) are an arrangement of computational elements consisting of a framework of input, hidden and output layers (Fig. 3). If the feed-forward BP algorithm is used, the goal is to find several connection weights, W_{ij}, such that the ANN learns to accurately map Input/Output pairs for a given training data set. Once the optimum weights have been found, the ANN is tested on an independent dataset, where the Input/Output associations learned previously are applied in a mathematical expression. This ANN modeling strategy is called "supervised learning". The basis for applying ANN trained thus is that the fundamental relationships between the input and output data are captured by the final optimum connection weights acquired during the training phase. During ANN training, each neuron computes a weighted sum of the inputs from the preceding layers as follows:

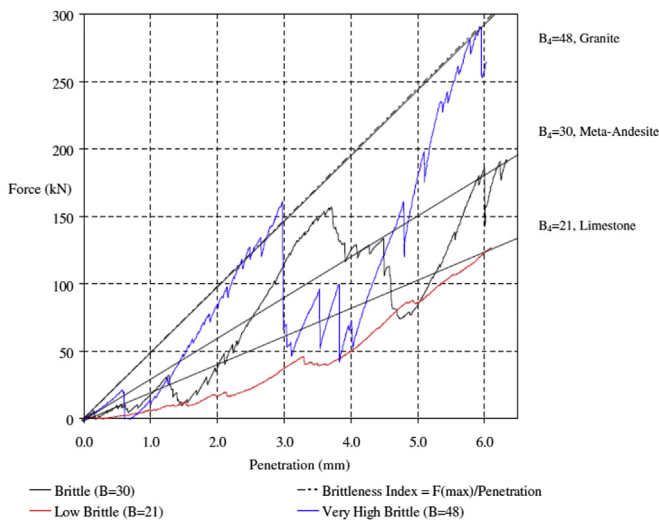$$X_i^{\mathrm{out}} = f\left(\sum_j W_{ij} X_j^{\mathrm{in}} + \theta_i\right) \qquad (3)$$

Fig. 2. Punch penetration test results showing force−penetration curves for three different rock types (Yagiz, 2009) with brittle index value, B. Note the brittleness can be related to the slope of each separate line.
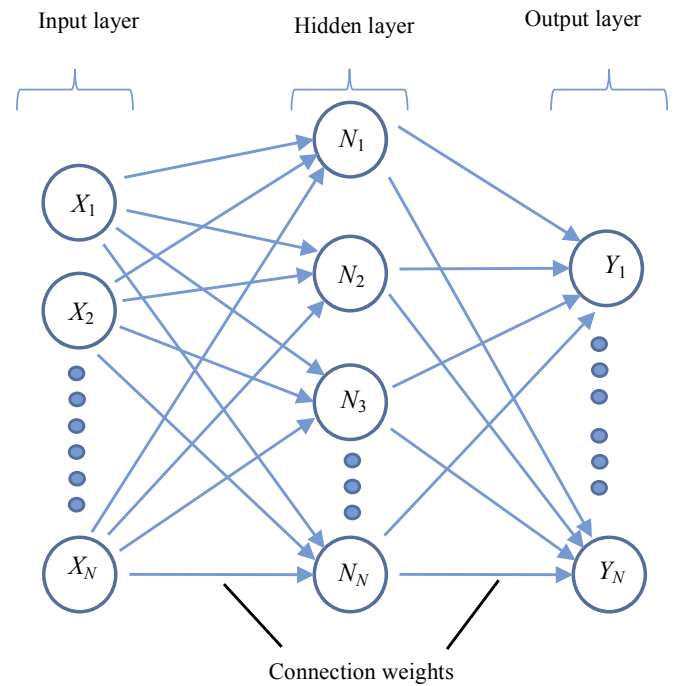
Fig. 3. Schematic of a feed forward ANN showing artificial neurons arranged as interconnected input, hidden and output layers.

where X_i^{out} is the output, $f(x)$ is a nonlinear transfer function such as the sigmoid function, X_j^{in} is the input, and θ_i is a constant called the bias.

The ANN training occurs by minimizing an error function defined as

$$ERR = \sum_p \sum_i \left[t_i^{(p)} - O_i^{(p)}\right]^2 \qquad (4)$$

where p is the pattern number, $t_i^{(p)}$ is the target output value, and $O_i^{(p)}$ is the neural network output value.

The error function is minimized iteratively using partial derivatives applied with respect to the weights and biases. In this study, the BP algorithm was implemented in MATLAB (MathWorks, 2014) on a standard PC (personal computer), and the results are reported in Section 3 and discussed in Section 4.

3. Results

The model results were obtained from the global database using the procedure as described in Section 2. Representative data from the global database used to develop the ANN model are shown in Table 1 with a total of 136 cases. The ANN model development strategy was implemented in two stages as follows: randomly
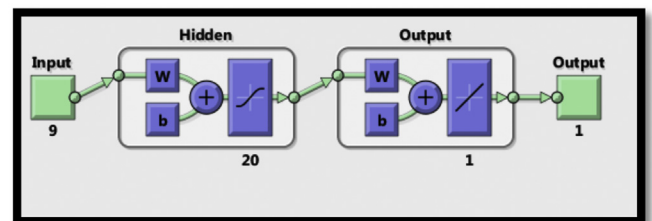
Fig. 4. Final neural network architecture showing 9 input neurons, 20 hidden neurons, and 1 output neuron (9 × 20 × 1 structure).
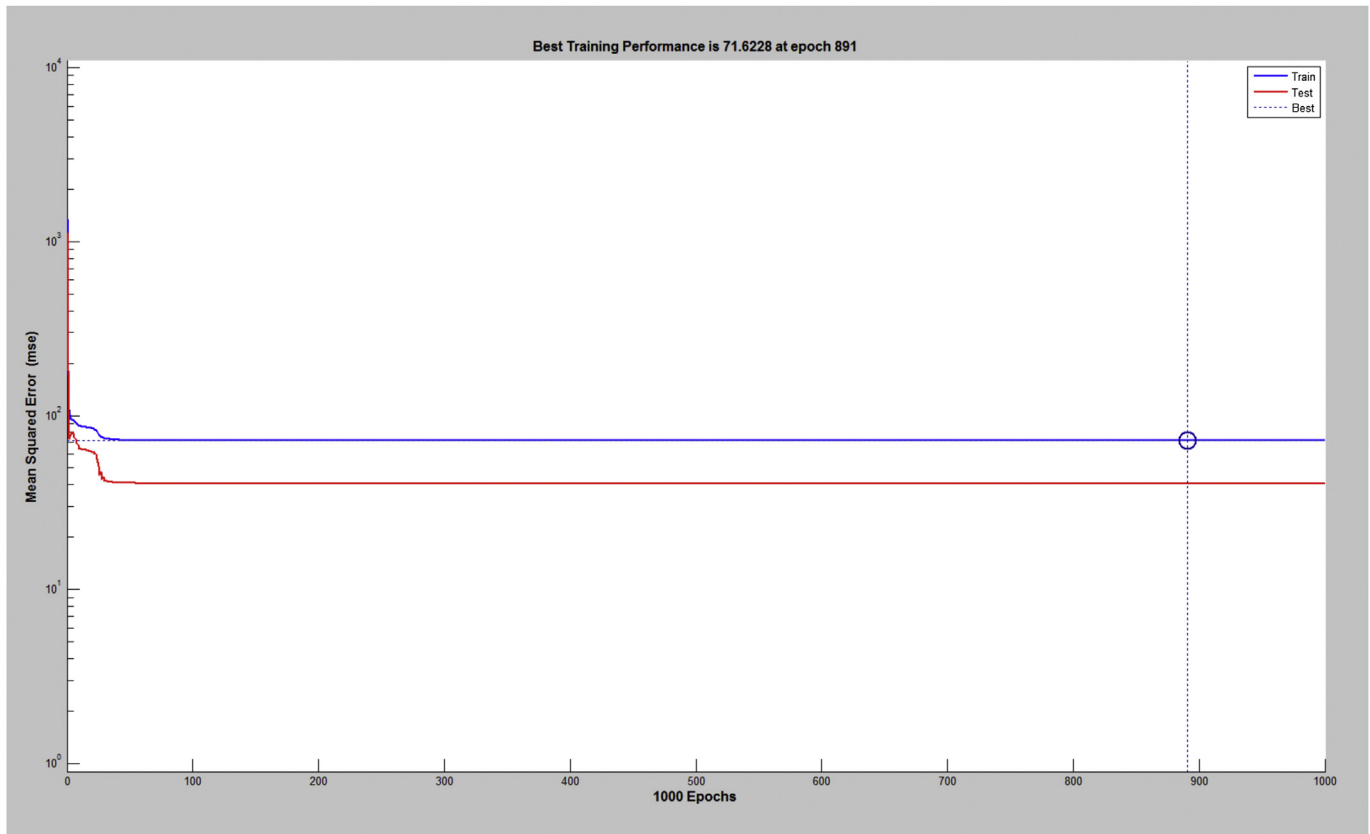
Fig. 5. Neural network performance during the training phase showing that the model converged after 890 epochs at minimum mean square error.

assign 85 cases for training and reserve 15 cases for model testing. For the number of neurons in the hidden layer, a heuristic approach starting with $\{2n + 1\}$ was applied as per recommended guidelines (e.g. Hecht-Nielsen, 1987). The original architecture was then modified to obtain the final configuration resulting in optimal performance resulting in a $9 \times 20 \times 1$ structure. The resulting optimum model architecture showing input, hidden and output layers is shown in Fig. 4.

The ANN training was implemented using BP with Bayesian regularization (MacKay, 1992). In the Bayesian framework, weights and biases are assigned random variables with specified distributions. Regularization parameters are then computed using the specified distributions and their associated variances. Regularization refers to modification of the performance function (i.e. Eq. (4)) resulting in reduced magnitudes of weights and biases for smoother network response. Fig. 5 shows that the ANN converged

Table 2
The final values of the ANN connection weights after supervised learning and training.

Neuron	Input layer-hidden layer connection weights									Output layer
	i1	i2	i3	i4	i5	i6	i7	i8	i9	
h1	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0831
h2	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0831
h3	−0.0071	0.0193	0.0393	0.0366	0.0195	−0.0086	0.0312	0.0068	0.0003	−0.0734
h4	0.0080	−0.0220	−0.0445	−0.0413	−0.0220	0.0099	−0.0352	−0.0077	−0.0004	0.0829
h5	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0832
h6	−0.0080	0.0221	0.0446	0.0414	0.0220	−0.0099	0.0353	0.0077	0.0004	−0.0831
h7	−0.0080	0.0221	0.0446	0.0414	0.0221	−0.0099	0.0353	0.0077	0.0004	−0.0831
h8	−0.0080	0.0220	0.0446	0.0414	0.0220	−0.0099	0.0353	0.0077	0.0004	−0.0831
h9	0.0080	−0.0221	−0.0446	−0.0414	−0.0220	0.0099	−0.0353	−0.0077	−0.0004	0.0831
h10	0.0079	−0.0219	−0.0442	−0.0411	−0.0219	0.0098	−0.0350	−0.0076	−0.0004	0.0824
h11	−0.5621	−0.0227	−0.1934	0.1606	0.2433	0.4604	−0.0460	0.2680	0.0938	0.5922
h12	−0.0080	0.0221	0.0446	0.0414	0.0221	−0.0099	0.0353	0.0077	0.0004	−0.0831
h13	−0.0080	0.0221	0.0446	0.0414	0.0221	−0.0099	0.0353	0.0077	0.0004	−0.0832
h14	−0.0080	0.0221	0.0446	0.0414	0.0221	−0.0099	0.0353	0.0077	0.0004	−0.0832
h15	−0.0080	0.0221	0.0446	0.0414	0.0220	−0.0099	0.0353	0.0077	0.0004	−0.0831
h16	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0831
h17	−0.0080	0.0221	0.0446	0.0414	0.0220	−0.0099	0.0353	0.0077	0.0004	−0.0831
h18	−0.0080	0.0221	0.0446	0.0414	0.0220	−0.0099	0.0353	0.0077	0.0004	−0.0831
h19	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0831
h20	0.0080	−0.0221	−0.0446	−0.0414	−0.0221	0.0099	−0.0353	−0.0077	−0.0004	0.0832

Table 3
The values of the biases used in the final ANN model.

Input-hidden layer biases	Value
B1	−0.0268
B2	−0.0268
B3	0.0238
B4	−0.0267
B5	−0.0268
B6	0.0268
B7	0.0268
B8	0.0268
B9	−0.0268
B10	−0.0266
B11	0.2244
B12	0.0268
B13	0.0268
B14	0.0268
B15	0.0268
B16	−0.0268
B17	0.0268
B18	0.0268
B19	−0.0268
B20	−0.0268
Output bias	−0.3370

after 890 epochs, when the values of the sum-squared error and the sum-squared weights reached constant values. Upon completion of ANN training, the final values of connection weights and biases were stored in the model and are shown in Tables 2 and 3, respectively. In other words, the mathematical expression of the final ANN model then becomes the one as shown in Eq. (3), with values of weights and biases displayed in Tables 2 and 3, and a hyperbolic tangent sigmoid transfer function yields

$$f(x) = \left[1 - e^{(-2x)} \right] \Big/ \left[1 + e^{(-2x)} \right] \qquad (5)$$

Fig. 6 shows the performance of the developed ANN model on test data that were set aside during training, compared with multiple regression analysis and the statistical model developed by Yagiz (2009). The multiple regression equation derived from the present database to predict brittleness index, *BI*, is:

$$BI = A + B(R) + C(\gamma) + D(P) + M(S) + F(\nu) + G(E) + H(L) \qquad (6)$$

where $A = -9.764$, $B = \{-24.4$ (metamorphic), -13.7 (igneous), -20.5 (sedimentary)$\}$, $C = -0.456$, $D = -0.032$, $M = 0.082$, $F = 75.1$, $G = -7.7 \times 10^{-10}$, $H = 9.14 \times 10^{-10}$; R is the rock type code (0−1); P is the P-wave velocity; S is the S-wave velocity; L is the Lame's constant.

Table 4 shows the corresponding errors with respect to the mean absolute error (MAE), mean square error (MSE), root mean square (RMSE), and normalized root mean squared deviation (NRMSD), and coefficient of correlation (R^2). The RMSE places emphasis on relatively larger errors, while the MAE eliminates such emphasis. The NRMSD is useful for typically comparing residual variances among data sets from different sources or scales.

Scatter plots and regression results are displayed on Fig. 7. The results show that the ANN model performs reasonably well with the highest coefficient of correlation, and with the lowest statistical error parameters compared to the other two methods. Smith (1986) provides the following guidelines with respect to R^2 values:

(1) $|R| \geq 0.8$, strong correlation exists between two sets of variables;
(2) $0.2 < |R| < 0.8$, correlation exists between the two sets of variables; and
(3) $|R| \leq 0.2$, weak correlation exists between the two sets of variables.

4. Discussion

All natural rock material contains defects, and the effective mechanical excavation involves strategic utilization of this characteristic. Therefore noninvasive (or non-destructive) methods, which provide some insight on intrinsic material brittleness prior to machine tool-rock face encounter, are highly desirable. In general, the higher the brittleness, the more efficient the crack initiation and propagation. The results reported herein indicate that if the rock type and rock density are known, it is possible to use acoustic velocities and elastic properties to characterize brittleness
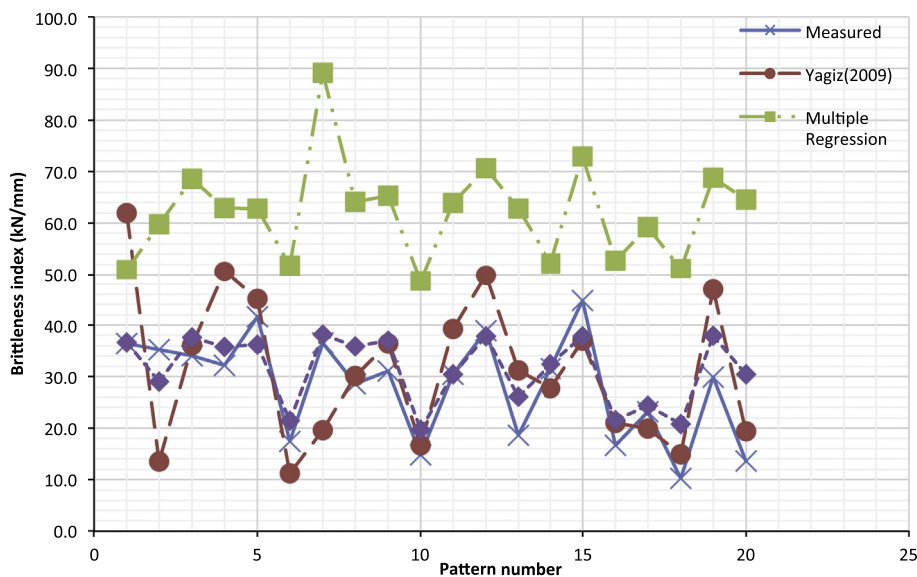

Fig. 6. Artificial neural network model test results compared with multiple regression and Yagiz (2009) model results.

Table 4
Model performance errors with respect to the MAE, MSE, RMSE, and NRMSD.

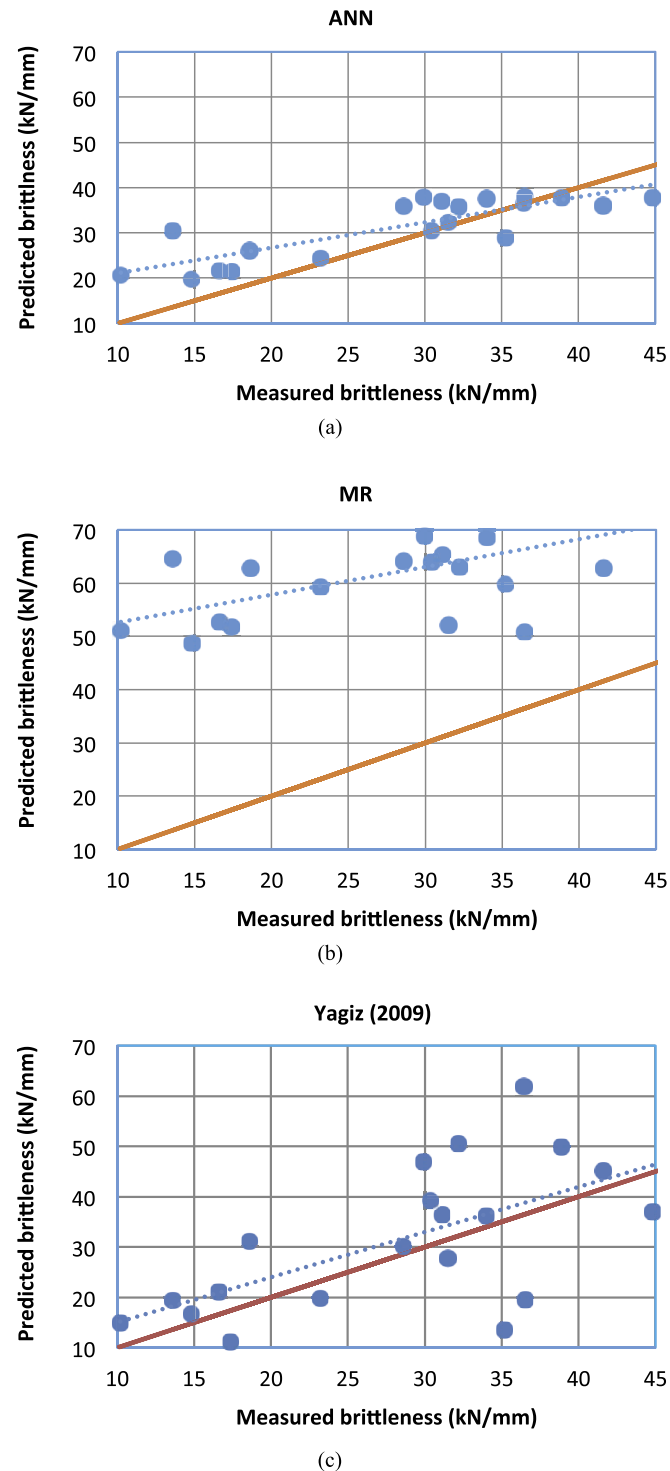| Model	R	MAE	MSE	RMSE	NRMSD
Yagiz (2009)	0.62	9.1	132.1	11.5	0.33
Multiple regression (MR)	0.54	22.9	1231.1	35.1	1.01
ANN	0.84	5.1	40.9	6.4	0.19

(a)

(b)

(c)

Fig. 7. Scatter plots and regression results for (a) ANN model, (b) multiple regression (MR), and (c) Yagiz (2009) statistical model. Note perfect correlation is represented by the 1:1 ratio solid line.

in a systematic manner useful to excavation engineers and other practitioners.

Further, elastic properties and elastic energy have strong correlations with rock brittleness (Tarasov and Potvin, 2013; Meng et al., 2015). Therefore it makes sense to apply P- and S-wave velocities to the prediction of the degree of brittleness as an intrinsic material property, as demonstrated herein. Given that rocks with the same intrinsic brittleness can behave differently under varying loading conditions and stress states, the method discussed in this study is not applicable to the assessment of "relative brittleness", where brittleness is regarded as a type of rock behavior and not a material property. For instance, Tarasov and Potvin (2013) reported from post-peak strength tests that sandstone became less brittle with increasing confinement, quartzite grew more brittle then less brittle with increasing confinement, and granite became less brittle before brittleness increased with increasing confinement. Meng et al. (2015) reported marble experienced decreasing brittleness and failure intensity with increasing confinement, while granite experienced no such change but more violent failure intensity instead.

In this study, sensitivity analyses were conducted to determine the most significant ANN input parameter, based on the cosine amplitude method (Bahrami et al., 2011):

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \tag{7}$$

where r_{ij} is the strength of the relation between two data pairs x_i and x_j, and reflects the strength of the relationship between the input and the output parameters.

In the cosine amplitude method, the higher the value of r_{ij} is, the greater the relationship between a specific input parameter and the model output is. Accordingly, as shown in Fig. 8, the three most significant input parameters to the ANN model are the P- and S-wave velocities and the unit weight. In terms of rock type, the ANN model is most sensitive to whether the rock is igneous, and least sensitive to whether the rock is sedimentary. The importance of the density and elastic constants in the performance of the ANN model is statistically similar, although they rank relatively higher than the "rock type" input parameters.

It should be noted that the Young's modulus values including Poisson's ratios used were predominantly dynamic, as they were obtained from the P- and S-wave velocity values. Prior to practical model application, care should be taken to ensure that any computed dynamic elastic properties are consistent with the representative static elastic properties, which was undertaken in this study. Material heterogeneity, micro-fracture density, porosity, mineralogy, moisture content, grain size, and crystal interlock all have important influences on intrinsic rock brittleness and hence mechanical excavation by extrapolation (Frank, 1998; Meng et al., 2015). The sensitivity analyses reported herein are consistent with the observations made by Hazzard and Young (2004) that seismic velocities can be related to rock modulus (stiffness). In brittle, low porosity rocks, micro-cracks tend to close under uniform loading, leading to higher seismic velocities. Under deviatoric loading, new cracks are formed and seismic velocities tend to decrease in perpendicular to the opening cracks.

The ANN model sensitivity analysis results also indicate that in terms of decreasing influence on prediction by rock type, the rank is igneous, metamorphic and sedimentary. This would be expected under normal conditions given that igneous rocks would be expected to be more brittle than metamorphic and sedimentary rocks. In other words, the results show that the current ANN model is more likely to better estimate the degree of brittleness for an
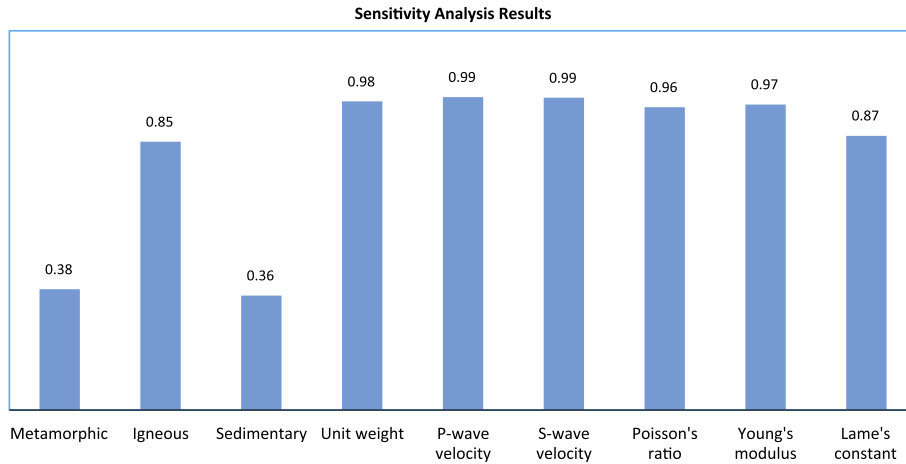
Sensitivity Analysis Results

Fig. 8. Sensitivity analysis results of r_{ij} values using the cosine amplitude method. Note the greater the magnitude, the higher the model sensitivity to an input.

igneous rock sample than for a sedimentary type. This would be expected given the distinct geologic histories and genesis of the two rock types in terms of homogeneity and mineralogical structure/composition. However additional rock tests and thin section analysis need to be conducted for a comprehensive assessment and systematic validation of such rock-type dependency.

5. Practical implications for mining and tunneling

The properties of intact rock such as brittleness have an important influence on predicting the penetration rates and advance rates of TBM. From a project planning and cost estimate perspective, prediction of TBM penetration rates is a key component (Farrokh et al., 2012). It is worthwhile therefore to provide some guidance on the utility of the ANN results discussed in the preceding sections although their emphasis has been on quantification of fundamentally intrinsic brittleness for specific rock types. Several models exist in the literature for the predictions of TBM penetration rates and advance rates in hard rock such as Rostami and Ozdemir (1993), Bruland (1998), Alvarez Grima et al. (2000), Yagiz (2002, 2008), and others. Eqs. (3) and (5) can be used to compute brittleness as a direct input in a typical penetration rate prediction model using the values given in Tables 2 and 3. However, the use of the ANN tool as a planning component should not preclude the use of more detailed assessments and investigations of brittleness that may be locally available for specific sites. For

instance, a more site-specific ANN could be developed using fewer relevant parameters based on local conditions. To demonstrate, the $9 \times 10 \times 1$ ANN architecture reported herein could be reduced to a $5 \times 10 \times 1$ ANN structure and still provide meaningful results for predicting brittleness as shown in Fig. 9. The reduced number of input parameters is represented by unit weight, γ, rock type, R, P-wave velocity, P, S-wave velocity, S, and Poisson's ratio, ν. The ANN model provides reasonable prediction on test data with relatively low errors. A multiple linear regression from the ANN model can be developed where the brittleness index, BI_r, is expressed by

$$BI_r = 2.02\gamma + 0.008P - 0.007S - 61.12\nu - 2.62R - 21.76 \quad (8)$$

While this simplified ANN model version is not as comprehensive as the first, it still provides the practicing engineer a very rapid preliminary means of estimating brittleness without the need for conducting UCS or tensile strength tests. The simplified version would then be improved by expanding the training database through addition of test results relevant to the site-specific field.

6. Conclusions

A new approach for the evaluation of intrinsic rock brittleness using noninvasive input parameters and ANN modeling has been introduced. The results show the ANN model is a better predictor of intrinsic rock brittleness than conventional destructive strength-test based models. Given that the ANN model is based on P- and
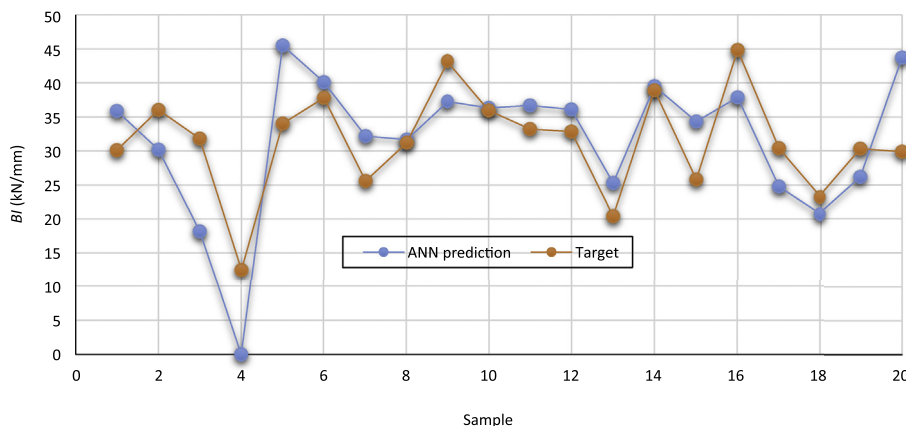

Fig. 9. Prediction results for ANN model with only five input parameters: unit weight, rock type, P-wave velocity, S-wave velocity and Poisson's ratio.

S-wave velocities, elastic properties can be accounted for. Currently the model is limited because it can only be applied to predictive performance on intact rock, and not directly applied to rock mass conditions during live mechanical excavation. Ideally, such direct application would be desirable as rock mass brittleness information could be obtained under inelastic conditions continually during machine operation in tunneling. However, in its present form, the technique could still be applied empirically. The current approach can also be extended to the modeling of additional rock properties and response to tunneling. Similar to intrinsic rock brittleness, these extensions would have implications on rock cutting and mechanical excavation in tunneling.

Conflict of interest

The authors wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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