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A preliminary application of a machine learning model for the prediction of the load variation in three-point bending tests based on acoustic emission signals

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Abstract

The load variation during three-point bending (TPB) tests on prismatic Nestos (Greece) marble specimens instrumented by piezoelectric sensors is predicted using acoustic emission (AE) signals. The slope of the cumulative amplitude vs the predicted load curve is potentially useful for determining the forthcoming specimen failure as well as the indirect tensile strength of the material. The optimum artificial neural networks (ANN) model was selected based on a comparison of different machine learning techniques with respect to the root mean square error (RMSE) and the coefficient of determination (CoD). The top three best-performing techniques were decision trees, random forests and artificial neural networks. Results show that decision trees and random forests have a coefficient of determination of 98.8% and 99.2%, respectively. The artificial neural network has an accuracy of 99.6% with a root mean square error of 0.022. The comparison of results with experimental data shows that ANNs can potentially be utilized to predict rock behavior and/or establish a failure index.

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1. Introduction

The indirect tensile strength of intact rocks is an essential mechanical parameter in rock mechanics and rock engineering. Because of the experimental difficulties and the developing shear stresses encountered in direct tension tests and Brazilian tests, the three-point bending (TPB) test was suggested by the International Society of Rock Mechanics (ISRM) for the determination of indirect tensile strength (Kaklis et al., 2009).

Prismatic Nestos (Greece) marble specimens were prepared and instrumented by piezoelectric sensors to record the acoustic emission (AE) signals during TPB tests. As a rock specimen is loaded to failure, a large number of such signals is generated. Since AE signals are caused by the formation, expansion and propagation of microcracks, such signals inherently include information related to the structural changes taking place within a rock sample (Kaklis et al., 2012, Nomikos et al. 2012). Previous studies on this marble have shown that during TPB tests less than 15-20% of the total AE activity was recorded for loads up to 75-80% of the maximum load, while AE signal generation increases rapidly for loads exceeding 75-80% of the maximum load (Agioutantis et al., 2016).

Machine learning is the study of computer algorithms that automatically improve through experience and by use of data (Mitchell, 1997). These algorithms build models based on sets of training data, and they make predictions without being explicitly programmed. They are used in a wide variety of applications such as self-driving cars, speech recognition, email filtering, holistic control of combined manipulators and modelling the state of mind (Mmereki et al. 2021, Malet et al. 2019).

Artificial neural networks (ANNs) were originally introduced by McCulloch and Pitts (1943). ANNs constitute a form of machine learning which attempts to mimic the function of the human brain and nervous system. ANNs learn from data examples presented to them that capture the subtle functional relationships among the data even if the underlying relationships are unknown or the physical meaning is difficult to explain (Shahin et al. 2008). A standard network structure has an input layer, hidden layer(s) and an output layer. Each layer contains processing units called neurons and each neuron is connected to the subsequent layer. All the layers are connected to each other by weighted connections. The three fundamental components of a neural network include the transfer function, the network architecture and the learning law (Simpson, 1990). Data submitted to ANNs are in the form of inputs and outputs; processing of the datasets determines the prevailing relationship(s). Several transfer functions such as *relu*, *tansig* and *logsig* are used by neurons to generate their outputs (Tiile, 2016).

The network is trained by processing large datasets. Although different algorithms are used for training, the back-propagation algorithm is the most popular due to its robust characteristics and ability to solve problems with vast complexities. It is also suitable for training multilayer feedforward networks with supervised learning techniques (Kalogirou, 2000). The principle of the backpropagation algorithm is to model a given function by modifying internal weightings of inputs to produce an expected output. The system is trained using a supervised learning method, where the error between the network's output and a known expected output is presented to the network and used to modify its internal weights. This process is known as model training and testing and it continues until the optimum model with minimum error is achieved (Monjezi and Dehghani, 2008).

In recent years, ANNs have been successfully applied by several researchers for modeling a variety of problems related to rock mechanics, rock engineering, geotechnical engineering (Shahin et al. 2001, Chao et al. 2018, Shahin et al. 2009) and mining engineering. Ferentinou and Fakir (2017), Wang et al. (2020) and Mohamad et al. (2015) used ANN algorithms to estimate the uniaxial compression strength of rocks by utilizing several mechanical parameters for different rock types. Rashidi et al. (2018) correlated the static and dynamic modulus, while Kaunda (2014) investigated the influence of the intermediate principal stress on the rock strength utilizing specially-designed ANN algorithms. The ground vibration and the air blast that was induced by blasting during mining operations at an open pit diamond mine were successfully predicted using ANNs by Kesalopa et al. (2019).

This paper discusses the variation of the load with respect to the AE amplitude signal. The slope of the cumulative amplitude vs the predicted load curve is potentially useful for determining the forthcoming specimen failure as well as the indirect tensile strength of the material. Different machine learning techniques are used to predict the load variation, in an effort to develop a procedure to quantify rock behavior under loading and/or establish a failure index. The top three best performing techniques were decision trees, random forests and artificial neural networks.

2. Material and experimental procedure

The indirect tensile strength under TPB tests was determined on beam specimens consisting of Nestos marble. This Greek marble is of white color with a few thin parallel ash-green colored veins containing locally silver areas due to the existence of dolomite (Kaklis et al., 2010).

The TPB tests were executed utilizing a 50 kN Triscan testing machine and a 50 kN load cell in specimens configured according to ISRM suggested methods, considered the plane of transverse isotropy. Six TPB tests were performed on beams of Nestos marble. The AE activity was detected through six miniature piezoelectric sensors mounted on the specimen's surface and recorded in an integrated multi-channel system. It should be noted that, the testing material, the experimental procedure as well as the setup and the location of the AE sensors were presented and described in detail in a previous research study by Agioutantis et al. (2016).

3. Acoustic emission analysis

Published data sets of previous research conducted by the same research group, (Agioutantis et al. 2016), are utilized in this study, by focusing only on the AE amplitude parameter. It was observed that during TPB tests, the AE signal generation increases rapidly for loads exceeding 75% of the maximum load (Fig. 1).

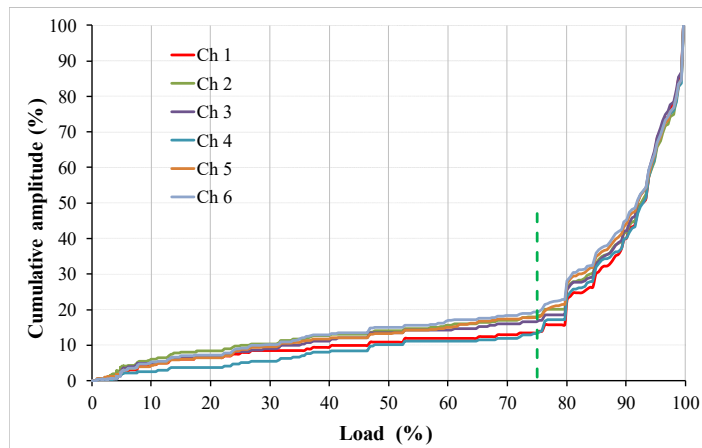


Fig. 1. Cumulative AE amplitude (%) for the Nestos marble specimen #7 with respect to percent TPB load. Data was recorded on six channels.

Fig. 2(a) presents the variation of the average cumulative amplitude with respect to load on each Nestos marble specimen, while the variation of the respective percentage values is presented in Fig. 2(b). It is clearly recognized that less than 20% of the total AE activity (defined as the critical AE level) was recorded for loads up to around 75% of the maximum load (defined as the critical load level). The rapid increase of the amplitude after the 75% load level, can potentially become a useful tool for determining the forthcoming specimen failure as well as the indirect tensile strength of the specimen.

Table 1 summarizes the mean value and standard deviation of the fracture load and the maximum average cumulative amplitude. Based on the average values of Table 1, the critical load level is 0.9 kN and the critical AE level is 1538 dB in terms of absolute values, meaning that up to a load value of 0.9 kN the recorded cumulative amplitude value is less than 1538 dB.

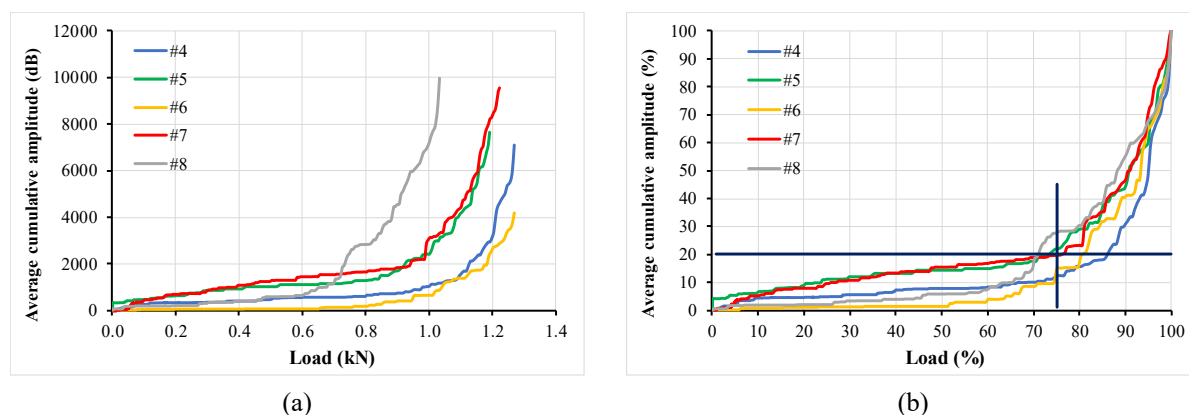


Fig. 2. Variation of the average cumulative amplitude for each specimen with respect to TPB load (a) and the variation of the respective percentage values (b).

Table 1. Experimental results for the TPB Nestos marble specimens.

Specimen	Fracture load (kN)	Maximum average cumulative amplitude (dB)
#4	1.27	7086
#5	1.19	7650
#6	1.27	4193
#7	1.22	9544
#8	1.03	9984
Average value	1.20	7691
Standard deviation	0.10	2307
#9	1.29	7380

4. Machine learning analysis

4.1. Comparison of machine learning models

A total of 1580 data pairs was provided, consisting of the acoustic emission signals (amplitude) and the load during five TPB tests (#4, #5, #6, #7 and #8). Model training utilized 85% of the available data pairs, while model testing was conducted using the remaining 15% of the available data pairs. A performance component analysis (PCA) algorithm was used for dimensionality reduction. For each test, the six channels of amplitude recorded by the piezoelectric sensors were reduced to one. The range of the input and output parameters is given in Table 2.

Table 2. Input and output parameters with their range.

Type of data	Parameters	Range
Input	Amplitude (dB)	0 – 14220
Output	Load (kN)	0 – 1.3

Several machine learning algorithms were applied to this data. The best performing algorithms included the artificial neural networks, the random forests (RF) and the decision trees (DT). For the training and testing of the datasets, the MATLAB and the Python programming language were used. MATLAB and Python include a wide array of tools that can be used for data processing, classification, regression, and visualization. As indicated above, model

testing was conducted using a dataset which was not used in the training process. Table 3 presents the coefficient of determination (CoD) and the root mean square error (RMSE) between the predicted and measured values for each algorithm and model.

Table 3. The CoD and RMSE of load variation by ANN, RF and DT models.

Model	CoD	RMSE
ANN		
Model 1 6-10-1 (transfer function=Tansig)	0.993	0.030
Model 2 6-15-1 (transfer function=Tansig)	0.996	0.022
Model 3 6-15-1 (transfer function=Relu)	0.973	0.060
RF		
Model 1 (10 trees)	0.898	0.056
Model 2 (30 trees)	0.968	0.041
Model 3 (60 trees)	0.992	0.036
DT		
Model 1 (max depth=4, min samples split=5, max leaf node=10)	0.862	0.089
Model 2 (max depth=6, min samples split=10, max leaf node=10)	0.942	0.065
Model 3 (max depth=10, min samples split=20, max leaf node=50)	0.988	0.041

The quality of model performance was examined based on the COD and RMSE values. Although all models are characterized by a quite high prediction ability, the ANN model #2 has the highest COD value of 0.996 and the lowest RMSE value of 0.022. This model was chosen to predict the load variation in TPB tests based on the acoustic emission signals, whereas prediction by the other models has a slightly wider variation.

4.2. Description of the proposed ANN model

A three-layer feed-forward back-propagation network type was developed to predict the TPB load. The input layer has six neurons, and the output layer has one neuron, whereas the hidden layer has several neurons. Levenberg-Marquardt was used as the training function, while different transfer functions to determine the optimum predictive model. The transfer functions used are Tan-sigmoid (tansig) and Relu. The learning rate was set to 0.001 and 1000 epochs. A typical structure of the neural network is shown in Fig. 3.

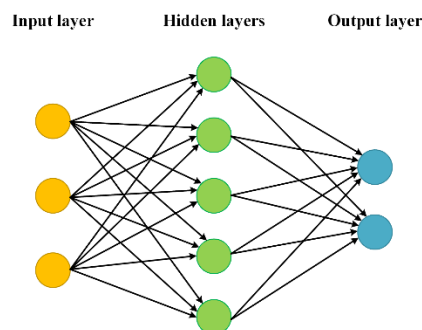


Fig. 3. Typical ANN model.

The ANN model #2 with a 6-15-1 network architecture and a tansig transfer function was found to be the optimum (Fig. 4(a)). Fig. 4(b) presents the relation between the predicted and measured load values for specimen #9, by the

optimum model on a 1:1 slope line. All the predicted data points are very close to the 1:1 slope line. This shows the predictive ability of this ANN for the TPB load.

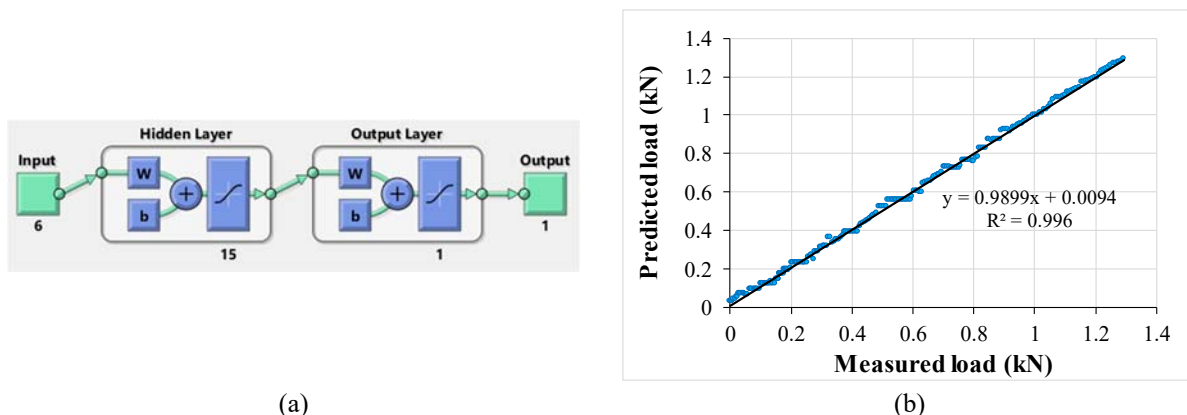


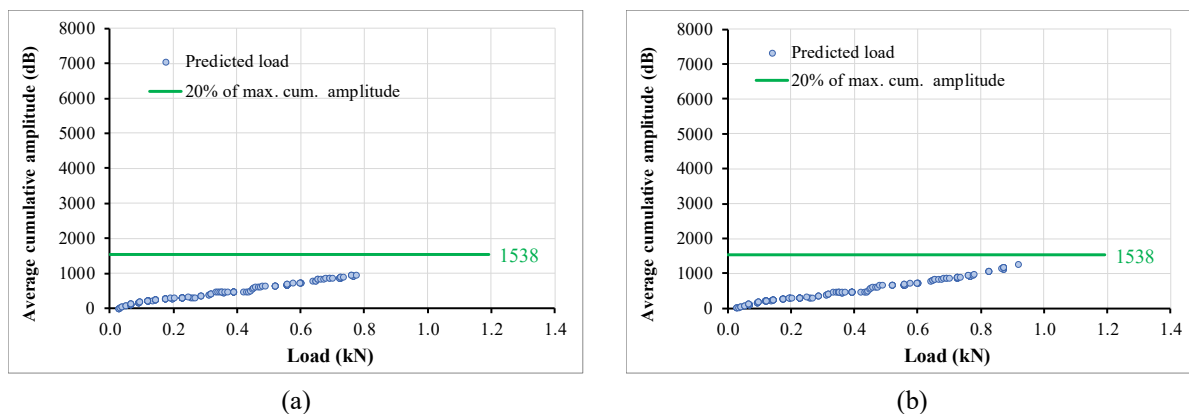
Fig. 4. (a) Optimum neural network architecture. (b) Predicted vs measured load values by ANN model 2 for specimen #9.

5. Results and discussion

The application of the proposed ANN model provides the predicted load time series for specimen #9. Fig. 5 presents the variation of the average cumulative amplitude with respect to the predicted load up to several percentage levels of the maximum load.

It is observed that the predicted load values do not exceed the critical AE level (1538 dB) up to 75% of the maximum load (Fig. 5(a) - (c)). After this critical load level, a rapid increase of cumulative amplitude is presented, while the slope of this curve increases rapidly up to the 100% of the maximum (fracture) load (Fig. 5(d) - (f)). The slope of this curve represents the function that relates the rate of cumulative amplitude change per unit change of load.

It is clearly shown that the proposed model can successfully predict the load variation in TPB tests on the Nestos marble, based on AE amplitude measurements (Fig. 5(f)).



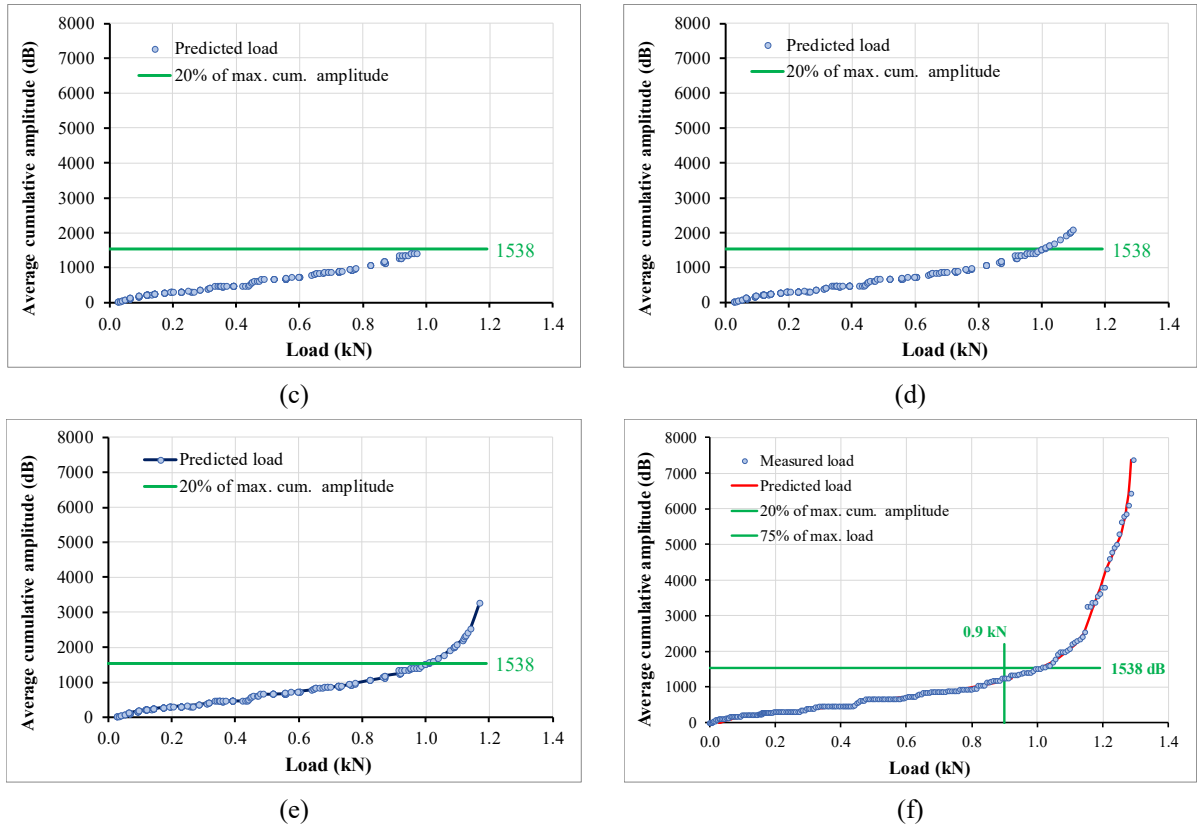


Fig. 5. Variation of the average cumulative amplitude for specimen #9 with respect to the predicted load, up to (a) 60%, (b) 70%, (c) 75%, (d) 85%, (e) 90%, (f) 100% level of the maximum load.

6. Conclusions

In this study, several machine learning algorithms were investigated to predict the load variation in three-point bending tests based on acoustic emission signals. The best performing algorithms included the artificial neural networks, the random forests and the decision trees. The overall best performing technique identified by this analysis was the ANN model #2 with a 6-15-1 network architecture and a tansig transfer function. This model shows the highest coefficient of determination (0.996) and the lowest root mean square error (0.022) compared to other models. As a result, this ANN model seems to provide an appropriate prediction of load variation under TPB tests on Nestos marble.

The comparison of the predicted load under TPB tests with the experimental data confirms the prediction capability of the proposed ANN model. The cumulative amplitude vs predicted load curve verifies the experimental critical AE and load levels, as well as the rapid slope increase of this curve. The ANN model can potentially be an appropriate tool to predict rock behavior, based on the experimental critical levels. During the TPB test, utilizing only the recorded AE signals, the critical load level could be identified and be used as a failure index of the material.

Based on this study, the proposed methodology could be confirmed and applied in various laboratory experimental procedures of rock mechanics and rock engineering. In the context of the new "Mining 4.0" era, a modified and properly designed ANN algorithm could predict the pillar and roof behavior/failure in several underground mining methods, based on acoustic or seismic recorded signals.

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