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Extended Abstract

Comparison of ANN–GA and linear regression for predicting rock failure strength under true triaxial stress

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Abstract

The intermediate principal stress (σ_2) plays an important role in rock failure under true triaxial stress conditions, yet its effect is not explicitly considered in many conventional two-dimensional failure criteria. This study compares a Genetic Algorithm-optimized Artificial Neural Network (ANN–GA) with multiple linear regression for predicting the major principal stress at failure (σ_1) using the intermediate and minor principal stresses (σ_2 and σ_3). A database comprising 212 true triaxial laboratory tests on five rock types was used for model development and evaluation. The ANN–GA model consisted of a feed-forward multilayer perceptron whose initial weights and biases were optimized using a Genetic Algorithm and subsequently trained using the Levenberg–Marquardt backpropagation algorithm. Model performance was evaluated using validation mean squared error (MSE) and five-fold cross-validation, while rock-specific and unified multiple linear regression models were developed for comparison. The ANN–GA model achieved validation MSE values ranging from 0.0001 to 0.007 across the investigated rock types, while the five-fold cross-validation resulted in a mean MSE of 0.059 ± 0.011. The rock-specific linear regression models provided strong fits to the experimental data, with R^2 values ranging from 0.93 to 0.96, whereas the unified regression model yielded an R^2 of 0.68. Given the differences in the evaluation procedures, these results are not interpreted as a direct statistical ranking of the two approaches. Instead, the ANN–GA model provides greater flexibility for representing nonlinear relationships among the principal stresses, whereas linear regression offers a simpler and more transparent alternative for rock-specific applications. The proposed data-driven framework may support rock failure assessment under true triaxial loading in deep underground excavations, tunnels, mining operations, and wellbore stability analyses.

1. Introduction

Rock masses in deep underground environments are subjected to complex three-dimensional stress states, making reliable prediction of rock failure strength essential for the design of tunnels, underground excavations, mining operations, and wellbores. Unlike conventional triaxial loading, true triaxial loading involves three unequal principal stresses, and the intermediate principal stress can significantly influence rock deformation, crack propagation, and failure strength. Experimental and numerical investigations have demonstrated that the effect of (σ_2) varies with rock type and stress conditions, highlighting the limitations of failure criteria that do not explicitly account for the intermediate principal stress [1–3].

Conventional failure criteria, such as the Mohr–Coulomb criterion, are widely used in rock engineering because of their relative simplicity. However, their ability to represent the complex response of rocks under true triaxial loading may be limited. Data-driven approaches, particularly artificial neural networks (ANNs), offer an

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alternative for modeling nonlinear relationships between stress variables and rock failure strength. Nevertheless, ANN performance depends on network architecture and parameter selection. Genetic Algorithms (GAs) can be employed to optimize network parameters and support the development of predictive models [4–8].

Despite advances in data-driven rock mechanics, comparisons between GA-optimized artificial neural networks (ANN–GA) and conventional regression methods using true triaxial experimental data remain limited. Accordingly, this study compares ANN–GA and multiple linear regression for predicting the major principal stress at failure (σ_1) from the intermediate and minor principal stresses (σ_2 and σ_3). The analysis uses 212 laboratory test records covering five rock types. The objective is to compare the predictive performance of linear and nonlinear approaches and examine their applicability to rock failure prediction under true triaxial loading, rather than to establish the inherent superiority of either method.

2. Methodology

A database of 212 true triaxial laboratory test records for five rock types—sandstone, Mizuho trachyte, KTB amphibolite, granite, and Dunham dolomite was compiled from previously published experimental data [8]. The numbers of records for these rock types were 44, 39, 46, 41, and 42, respectively. The intermediate and minor principal stresses (σ_2 and σ_3) were used as input variables, while the major principal stress at failure was selected as the prediction target. The input variables were normalized to the range [0, 1] using min–max normalization.

For each rock type, a separate feed-forward multilayer perceptron (MLP) was developed, comprising two input neurons, three hidden layers, and one output neuron. Sigmoid activation functions were used in the hidden layers, and a linear activation function was employed in the output layer. A Genetic Algorithm was used to optimize the network weights and biases, followed by training with the Levenberg–Marquardt backpropagation algorithm. The GA settings included a population size of 30, a maximum of 100 generations, and 15% elitism. Single-point crossover, Gaussian mutation, and negative MSE as the fitness function were also specified. The hidden-layer architecture was selected separately for each rock type through a trial-and-error procedure. During network training, 15% of the data were reserved for validation.

ANN–GA performance was evaluated using the mean squared error (MSE). In addition, five-fold cross-validation was performed on the combined dataset to examine the model's performance across different data partitions. For comparison, multiple linear regression models were developed using the same two input variables. Separate regression equations were fitted for individual rock types, and a unified regression equation was developed using the combined dataset. Regression performance was evaluated using the coefficient of determination ((R^2)), root mean squared error (RMSE), and mean relative absolute error (MRAE). Because the evaluation procedures were not identical, the results were interpreted in terms of the observed performance of each approach rather than as a definitive statistical ranking.

3. Results and Conclusions

The experimental data indicated that the relationship between the intermediate principal stress and the major principal stress at failure differed among the five rock types. Sandstone and Mizuho trachyte exhibited comparatively limited changes in σ_2 as σ_1 increased, whereas KTB amphibolite, granite, and Dunham dolomite generally showed more pronounced responses. For Dunham dolomite, σ_1 generally increased with σ_2, although this increase became less pronounced at higher values of the minor principal stress, and a slight reduction was observed at the highest σ_2 levels. These observations highlight the dependence of the stress–strength relationship on lithology and stress conditions.

For the selected ANN–GA architectures, the reported training MSE values ranged from 0.00008 to 0.02, while the validation MSE values ranged from 0.0001 to 0.007. Five-fold cross-validation on the combined dataset yielded a mean MSE of (0.059 ± 0.011). These results provide complementary measures of model performance under the reported training, validation, and cross-validation procedures. However, the MSE values from these procedures should be compared directly only after confirming that they were calculated on the same target scale and under consistent evaluation conditions. The results suggest that ANN–GA can represent complex

relationships between the principal stresses without imposing a predefined linear functional form, although its generalization capability requires further assessment using independent data.

The rock-specific multiple linear regression models achieved (R^2) values ranging from 0.93 to 0.96, whereas the unified regression model developed from the combined dataset yielded an (R^2) of 0.68. This difference indicates that a single linear equation may not adequately represent the variability across the five rock types. Nevertheless, because the ANN–GA and regression models were not evaluated using fully identical procedures, these results do not establish the statistical superiority of one approach over the other. Rather, they illustrate the potential of nonlinear modeling and the practical value of simpler, rock-specific regression equations.

Overall, this study presents a comparative assessment of ANN–GA and multiple linear regression for predicting rock failure strength under true triaxial loading. The findings may support preliminary analyses of rock strength in underground engineering applications. However, the database is limited to 212 laboratory records from five rock types, and the results should be interpreted within the range of the available experimental conditions. Further work should incorporate additional lithologies, broader stress ranges, independent experimental datasets, and consistent validation procedures to assess predictive reliability and generalization. Moreover, extrapolation from intact laboratory specimens to natural rock masses requires caution because discontinuities, anisotropy, fluid pressure, stress path, and scale effects may influence field behavior.

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5. References

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