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APPLICATION OF NEURAL NETWORKS FOR OPTIMIZING ROCK BOLT SYSTEM IN UNDERGROUND MINING

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Abstract

This paper explores the application of artificial neural networks (ANN) in optimizing drift support systems in underground mining. Using input parameters such as rock bolt length, diameter, and quantity, a multilayer ANN model was developed to predict key stability indicators: total displacement and safety factors. The model was trained and validated using numerical simulation results based on finite element analysis. The ANN demonstrated high accuracy and generalization capability, providing a reliable tool for decision-making in geotechnical design.

Keywords: *neural networks, rock bolt system, underground mining*

1. INTRODUCTION

Rock bolting is a widely used method for stabilizing underground excavations due to its adaptability, cost-effectiveness, and ability to support staged excavation. Optimal design of rock bolts considering length, diameter, density, and tension is crucial for site-specific stability but remains challenging due to varying geological and stress conditions [1]. Artificial neural networks (ANNs) have recently emerged as powerful tools in geomechanical engineering, capable of modeling complex, nonlinear relationships. They have shown high accuracy in predicting deformation and stability outcomes in tunnels, slopes, and retaining walls. In several studies, ANNs trained on finite element method (FEM) data have acted as efficient surrogate models, providing predictions that closely match numerical results while drastically reducing computation time. These speed and accuracy benefits make ANNs suitable for iterative optimization tasks in geotechnical design. In underground mining, the use of ANNs for support system design is still developing. However, initial studies show they can outperform traditional empirical models in predicting optimal bolt parameters [2, 3, 4].

This paper presents an ANN-based predictive model for optimizing rock bolt support systems in underground drifts. FEM simulations are used to generate training data for various bolt configurations, and the ANN learns to predict drift displacement and safety factor outcomes. The methodology, model architecture, and validation results are presented and compared to FEM benchmarks to evaluate the potential of this approach for practical mining applications.

2. EXPERIMENTAL

The study considered a section of an underground drift (mining room) excavated in the T3 ore body at the Jama Bor mine, which requires a rock bolt support system. A numerical model of the drift was created using finite element method (FEM) software to simulate the rock mass behavior and support interaction. The drift was approximately 4.5 m in width and 4.3 m in height, situated in andesite host rock (hydrothermally altered) with geomechanical properties characterized by prior site investigations. The Hoek–Brown failure criterion was used to represent rock mass strength, as it provides a reliable approximation for heavily jointed rock masses and was found to yield accurate safety factor estimates in this context.

A series of numerical experiments was conducted, varying three key rock bolt parameters within practical ranges:

- Bolt length (embedded length in rock), in the range 1.6 – 2.2 m.
- Bolt diameter, in the range 22 – 24 mm.
- Number of bolts in the drift crown, from 8 to 10 (per 4.5 m width of drift).

Using a full factorial combination of these parameters, 16 different support configurations (models) were analyzed (each corresponding to a unique combination of length, diameter, and number within the given ranges). For each model, the FEM simulation provided two primary outputs of interest: (1) the maximum wall displacement in the surrounding rock (i.e. the convergence of the drift walls in meters), and (2) the factor of safety (FS) of the rock mass around the opening, as computed by the shear strength reduction technique. The maximum displacement values obtained from the numerical models ranged from about 7.2 mm up to 13.9 mm, while the safety factor ranged from about 1.02 (in the weakest support case) up to 1.55 (in the strongest support case). All displacement values fell within a generally acceptable convergence limit (on the order of 1 cm or less) for a drift of this size, indicating that even the minimal support case was just at the threshold of acceptability. The trends observed were intuitive: increasing bolt length, diameter, or quantity tended to reduce the maximum displacement and increase the safety factor of the drift. For example, the worst-case support (shortest, thinnest, fewest bolts: 1.6 m × 22 mm, 8 bolts) yielded 13.9 mm convergence and FS ≈ 1.02, whereas the best-case support (longest, thickest, most bolts: 2.2 m × 24 mm, 10 bolts) reduced convergence to 7.2 mm and raised FS to 1.55 (a comfortably stable condition). These FEM-generated results formed the supervised learning dataset for the neural network model.

A feed-forward artificial neural network was designed to map the rock bolt parameters to the resulting displacement and safety factor. The network input layer has three neurons corresponding to the three input variables: bolt length, bolt diameter, and number of bolts. The output layer has two neurons, producing the predicted maximum displacement (continuous value) and predicted safety factor for a given set of inputs. After experimenting with a few configurations, a single hidden layer with five neurons was selected, as it provided sufficient model capacity to fit the data without overfitting (given the relatively small dataset).

The network was implemented in MATLAB using the Neural Network Toolbox. Prior to training, all input and output values were normalized to a similar scale (0 to 1) to aid convergence. A Levenberg–Marquardt backpropagation algorithm was employed for training, as it is known for fast convergence in small- to medium-sized networks. The transfer functions in the hidden and output neurons were differentiable sigmoid and linear functions, respectively, to meet the requirements of the training algorithm. The 16 available data samples were used to train and validate the network. To make the most of the limited data, we used a leave-one-out cross-validation strategy: at each iteration, 15 samples were used for training and 1 held-out sample for validation/testing, cycling through all samples. The network weights were initialized with small random values, and the training proceeded until the performance goal was met (mean squared error, MSE, below 10^{-4}) or no further improvement was seen on the validation sample. Regularization (Bayesian regularization in MATLAB) was applied to prevent overfitting given the small dataset. Training was successfully completed with rapid error reduction – the final model achieved a mean squared error on the order of 10^{-5} and an excellent fit to the data. Figure 1 shows the correlation between the ANN's predicted outputs and the target values from FEM for all data points. The points lie almost on the 45° line, and the correlation coefficient R for both outputs is over 0.99, indicating that the network has learned the relationship extremely well. In essence, the

ANN can reproduce the FEM results of maximum displacement and safety factors with very high fidelity for the cases it was trained on.

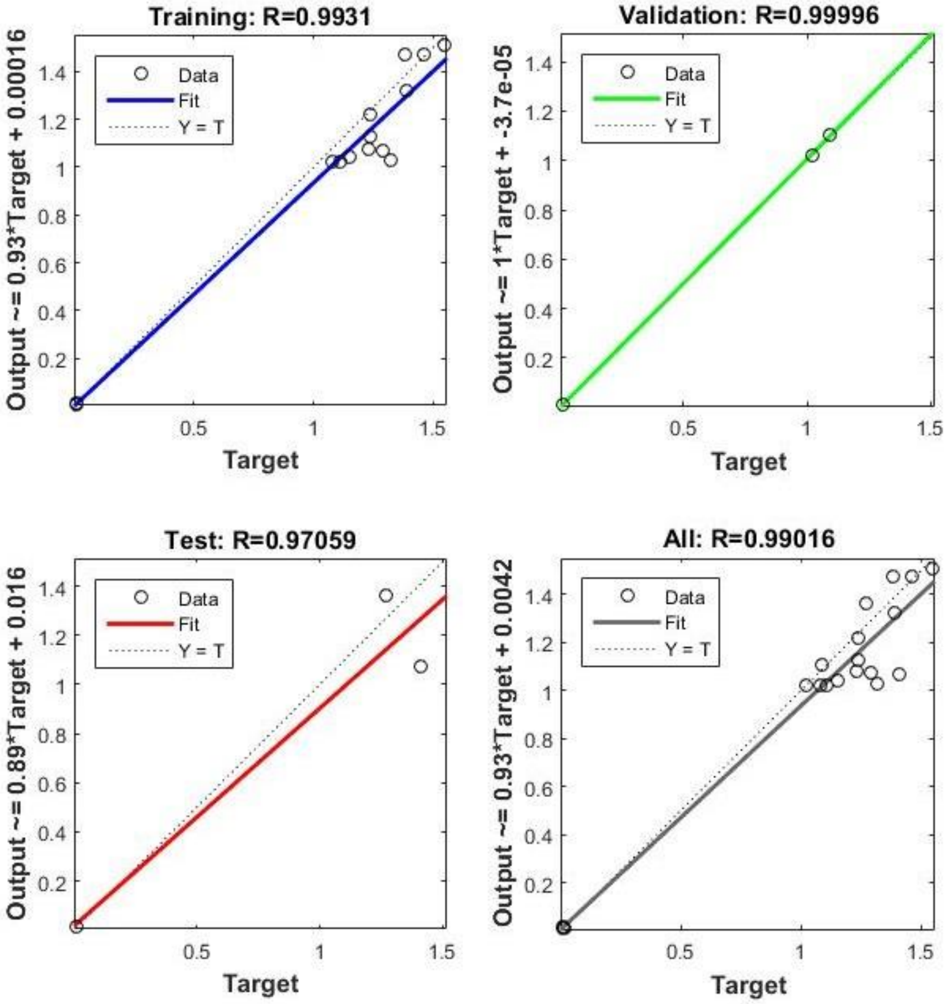

Figure 1. ANN prediction performance: correlation of network-predicted vs. FEM-calculated values. The plots show that the predicted maximum displacement and safety factor closely match the target values (all points near the diagonal), with correlation coefficient R ≈ 1.0 for both outputs, demonstrating excellent learning of the input-output mapping.

3. RESULTS

After training, the ANN model was used to predict the outcomes for new support parameter inputs. As an initial test, the ANN was tested on a new scenario (Model A) with support parameters outside the training set: bolt length 1.4 m, diameter 27 mm, and 9 bolts. The ANN predicted 12.2 mm displacement and a safety factor of 1.1518. FEM analysis of the same case yielded similar results: 11.8 mm and 1.147, confirming high prediction accuracy (Table 1). This strong match shows that the ANN can reliably estimate ground response, offering a fast alternative to time-consuming FEM simulations. Once trained, the network instantly predicts drift stability for different support setups, enabling rapid optimization. The ANN captures realistic behavior, such as reduced displacement with longer/thicker bolts and diminishing returns. It serves as a model useful for parametric studies and design decisions. However, its accuracy depends on the quality and scope of the FEM training data. For new geological settings, retraining may be required. Despite being trained on only 16 samples, the ANN generalized well thanks to its simple structure and regularization. In conclusion, ANN models can significantly accelerate and enhance support design in underground mining by replacing repetitive simulations with intelligent prediction, improving both safety and cost-efficiency. This scenario, called Model A, used intermediate or slightly extrapolated values: bolt length 1.4 m (shorter than any training sample), bolt diameter 27 mm (thicker than any training sample), and number of bolts 9.

The network, when given Model A inputs, predicted a maximum displacement of 0.0122 m (12.2 mm) and a safety factor of 1.1518 for the drift. To verify these predictions, a full FEM analysis was then conducted for the same support scenario. The FEM results for Model A indicated a maximum displacement of 0.0118 m (11.8 mm) and a safety factor of 1.147.

Table 1. Comparison of ANN prediction and FEM result for a new bolt configuration (Model A: bolt length 1.4 m, diameter 27 mm, number of bolts 9).

	ANN		Finite Element Method (Phase)	
Model	Total displacement	Safety factor	Total displacement	Safety factor
	(m)	/	(m)	/
A	0.0122	1.1518	0.0118	1.147

4. CONCLUSION

This paper presented an ANN-based method for optimizing rock bolt support in an underground drift, using data from FEM simulations at the Jama Bor mine. The trained neural network accurately predicted maximum displacement and safety factors across various support configurations, achieving high level of correlation with FEM results and generalizing well to unseen scenarios. The ANN proved to be an effective surrogate model, enabling rapid support system optimization without the need for repeated numerical simulations. It offers immediate predictions, helping engineers identify optimal bolt setups with minimal effort and high reliability.

The method is adaptable to other mining projects by generating a small set of FEM data specific to local conditions. This fusion of numerical modeling and AI improves design efficiency, supports safer excavations, and aligns with the broader trend of smart mining technologies.

Future work may expand the input space (e.g., bolt spacing, stiffness, rock quality) or integrate hybrid models and optimization algorithms to further enhance predictive power and design automation.

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