Predicting Burden Rock Velocity in Limestone Mines using Artificial Neural Network Models

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Abstract
The prediction of burden rock velocity is crucial in optimizing the efficiency of mining and excavation operations. This study presents a novel approach utilizing Artificial Neural Networks (ANNs) to accurately predict the velocity of burden rocks based on various input parameters such as rock property, geological property and bench properties. A comprehensive dataset was collected from field measurements and laboratory experiments to train the ANN models. The performance of the ANN models such as Multi-layered Perceptron (MLP), Deep Neural Network (DNN), simple MLP and Backpropagation Neural Network (BPNN) was evaluated based on performance metrics R-squared $(R)^2$, Mean Squared Error (MSE) and Mean Absolute Error (MAE). Among the developed ANN models, the BPNN model was found to be the most accurate predictive model for burden rock velocity, as evidenced by metrics R2(0.821), MSE (0.099) and MAE (0.226).

The results indicate that the BPNN model effectively captures the complex relationships between the predictors and burden rock velocity. Advanced neural network algorithms such as recurrent neural networks and long short-term memory techniques can be used to improve the accuracy of presented neural network models.

Keywords: Artificial neural network (ANN), Backpropagation neural network (BPNN), Burden rock velocity, Deep neural network (DNN).

Introduction
In the mining and excavation sector, the efficiency and safety of blasting operations are profoundly influenced by the movement dynamics of burden rocks[7,19]. The velocity of these rocks plays a pivotal role in determining material handling strategies, optimizing blast designs and enhancing overall productivity[20]. Accurate prediction of burden rock velocity is critical as it enables more effective resource management, streamlined workflows and a significant reduction in operational costs[8].

Furthermore, precise predictions contribute to minimizing environmental impacts by ensuring better control over blasting outcomes, reducing the likelihood of overburden displacement and mitigating ecological disturbances[6]. Traditional methods for estimating burden rock velocity typically rely on empirical formulas and observational data. While these approaches provide a general understanding, they often fall short of capturing the intricate and nonlinear interactions among geological, operational and environmental factors[3,9]. The increasing complexity of modern mining operations demands advanced predictive techniques that can account for these multidimensional influences. This has fueled a growing interest in utilizing technological advancements, particularly artificial intelligence-based predictive modeling, to improve predictive accuracy and operational decision-making [11].

Artificial Neural Networks (ANNs) have emerged as a promising alternative to conventional methods. Unlike traditional techniques, ANNs excel at modeling complex, nonlinear relationships and can effectively learn patterns from extensive datasets [16]. By integrating diverse input variables such as rock type, density, environmental conditions, blasting parameters and historical performance data, ANNs provide a holistic and data-driven approach in understanding the factors influencing burden rock velocity. This ability to analyze multifaceted interactions makes ANNs invaluable tools for addressing the challenges of modern mining operations, offering deeper insights and more reliable predictions [17].

This study focuses on developing and validating ANN-based models such as Deep MLP, DNN, simple MLP and BPNN using input parameters such as rock, geological and bench properties. The novelty of this study lies in the comprehensive exploration of ANN architectures tailored specifically for predicting burden rock velocity, incorporating a diverse range of geological and operational parameters.

Review of Literature
Accurate predictions of burden rock velocity are crucial for improving operational efficiency in mining and geotechnical engineering. Various predictive artificial neural network (ANN) techniques have been explored in the literature, each with unique advantages and applications. Recent studies have employed ANNs for predicting outcomes such as rock fragmentation, peak particle velocity and fly rock in mining operations, demonstrating their versatility and effectiveness[4,15,17].

Backpropagation Neural Network (BPNN) is an artificial neural network that utilizes a supervised learning algorithm to model complex relationships within the data. They are widely employed in various fields including engineering, finance and medicine, due to their ability to learn from examples and make accurate predictions based on input data. The BPNN architecture consists of multiple layers of interconnected nodes (neurons), typically organized into three main layers: an input layer, one or more hidden layers and an output layer. BPNNs have been used in mining to optimize blasting operations and predict rock behavior[14].

MLPs are feedforward neural networks consisting of an input layer, one or more hidden layers and an output layer. They can model non-linear relationships and are widely used for regression tasks. However, MLPs may require large datasets and computational power for effective training. They are typically trained using the backpropagation algorithm. A few studies utilized MLPs to predict rock fragmentation and to assess blast-induced forces' impacts[1,2].

DNNs extend MLPs by adding more hidden layers, allowing the model to capture complex hierarchical patterns. While they can provide higher accuracy for complex tasks, they are prone to overfitting and require careful regularization and optimization techniques. DNNs have paved the way for a good approach in predicting burden rock velocity to optimize rock blasting operations. One such study by Zang[19] includes developing DNNs to model complex relationships between blast hole diameter, explosive charge rock properties and burden rock velocity, leading to more accurate predictions than traditional empirical methods.

Simple MLPs have fewer hidden layers than typical MLPs, making them more efficient in terms of computation. These networks are suitable for simpler regression tasks and smaller datasets, balancing performance and training efficiency well. They are particularly effective in scenarios where computational resources are limited such as small-scale mining projects[12].

Case study: Field investigations were conducted at three limestone mines designated mine A, mine B and mine C to collect the samples and relevant data. The spatial distribution of these mines, located in Telangana and Andhra Pradesh districts, is depicted in the satellite imagery presented in figure 1. The bench heights across the study sites varied between 6 -10 m. The exposed limestone formations predominantly exhibited grey to off-white coloration and were characterized by a fine-grained texture. The deposits displayed distinct bedding features with variable thickness and were observed to be significantly fractured, indicating structural discontinuities.

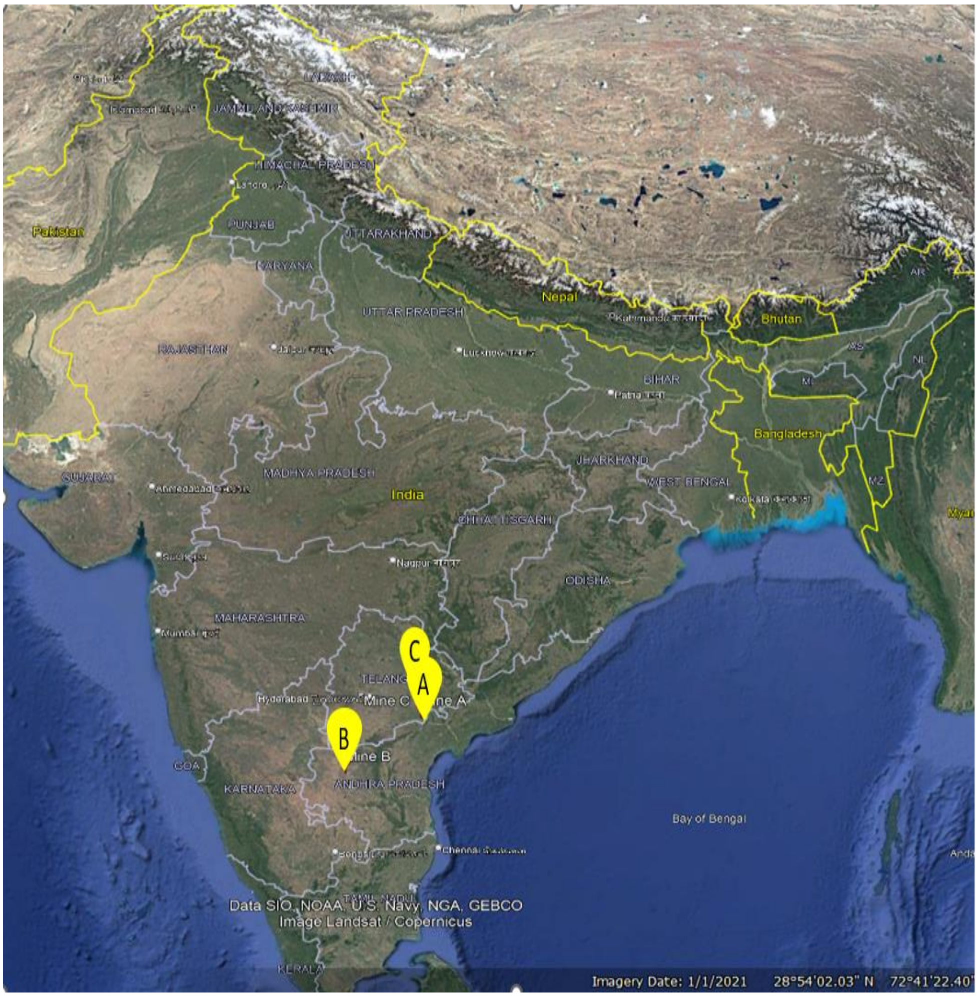

Figure 1: An aerial satellite image view of the location of all three limestone mines.

In the blasting operation of the mine, a total of 166 blasts were conducted using the benching method in all three mines, with bench heights ranging from 6-10 m. Drilling and blasting techniques involve 115 mm diameter blast holes drilled at a 15° inclination. Blastholes, 6.5-10m deep, are charged with ANFO mixed with husk to reduce charge concentration, using 'Ideal Boost' as a primer and Excel Dueldet shock tube detonators for precise initiation. The remaining 2 -2.75 m of the blastholes stem from inert drill cuttings before interconnection and blast preparation. Highspeed videography captures rock breakage and movement during blasting, which occurs too rapidly to be observed by the naked eye.

The recorded videos are analyzed using Proanalyst software to measure burden rock movement to calculate its velocity based on the time taken by rock particles to travel specific distances. Calibration is performed using a known reference, such as burden distance or bench height. Among the measured velocities at the top, center and toe, the center velocity is consistently highest, serving as the most representative indicator of blast effectiveness.

Material and Methods

This study applies machine learning approaches to predict burden rock velocity using neural network architectures. Four distinct neural network models were developed and evaluated: Deep Multi-Layer Perceptron (Deep MLP), Deep Neural Network (DNN), Simple Multi-Layer Perceptron (Simple MLP) and Backpropagation Neural Network (BPNN). In the present study, a schematic of the general architecture of the neural network and back propagation neural network models is shown in figure 2 and figure 3. The seven key input features were identified as critical for model training: Blast Hole Diameter (BH), Charge per Delay (CPD), Total Explosive Consumption (TEC), Stiffness Ratio (K), Powder Factor (PF), Joint Spacing (JS) and Point Load Index (PL). The input features and their respective ranges are provided in table 1 while table 2 outlines the range of output parameters considered for analysis.

Table 1
Input parameters for the network along with their respective ranges

S.N.	Input Parameters	Range
1	Bench height (BH)	6.5-11 m
2	Charge per Delay (CPD)	30.7-89.4 kg
3	Total Explosive Charge (TEC)	649.5-2808.9 kg
4	Stiffness Ratio (K)	2.9-5.1
5	Powder Factor (PF)	3.5-8.5 t/kg
6	Joint Spacing (JS)	12-23 cm
7	Point Load Index (PL)	2.5-5.5 MPa

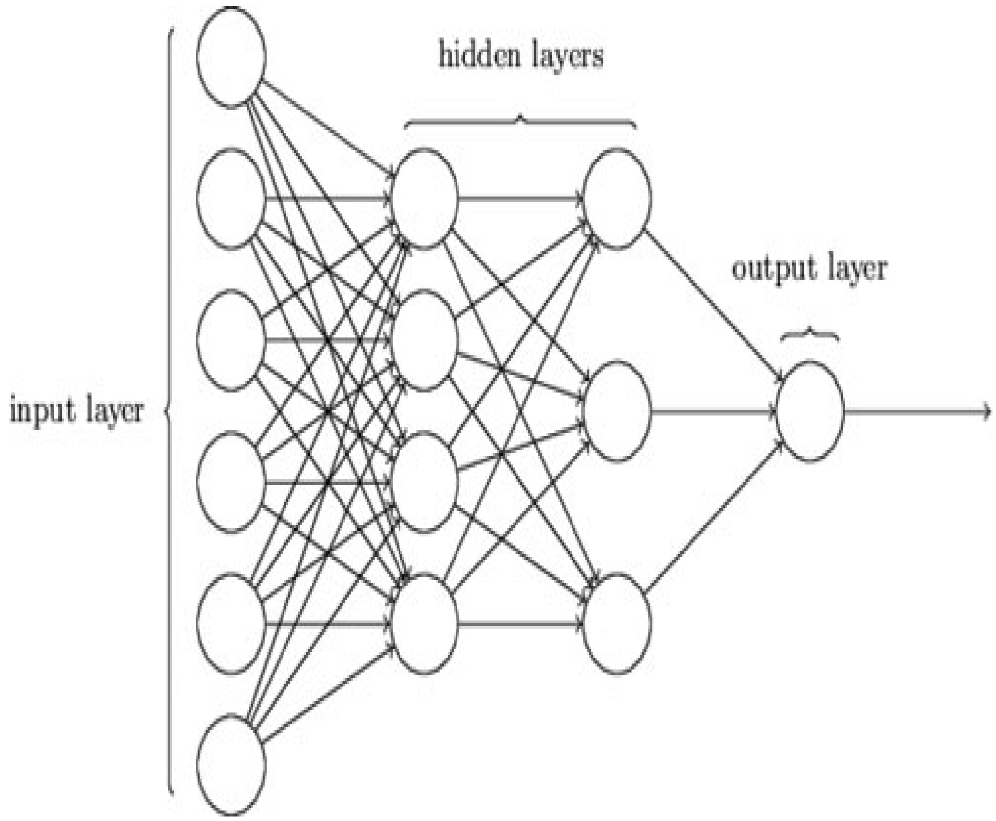

Figure 2: The general architecture of neural networks consists of an input, hidden and output layer.

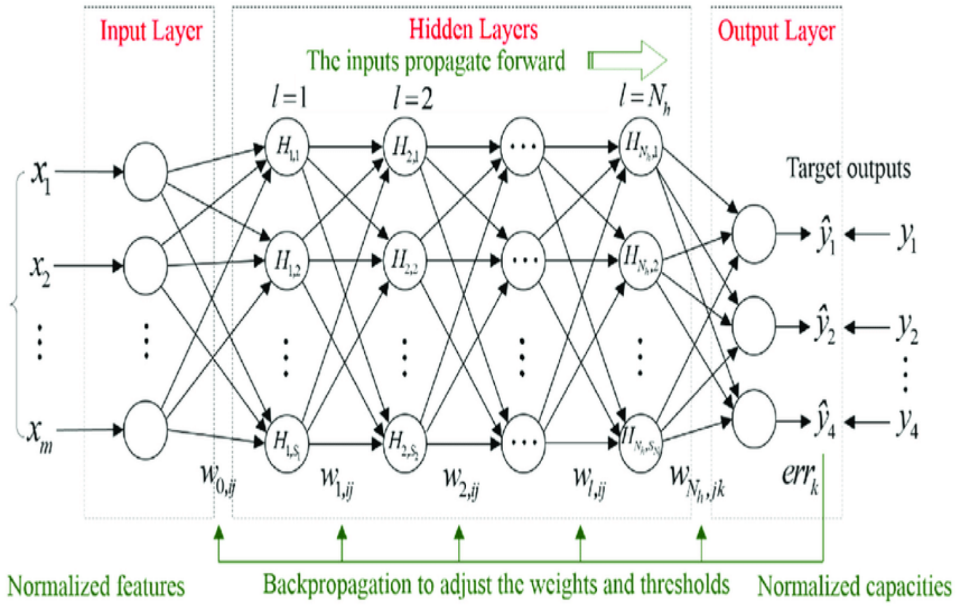

Figure 3: The general architecture of a backpropagation neural network, x is the input values, H is the hidden nodes and ŷᵢ are the predicted values against the actual values y.

Table 2
Output parameters for the network along with their respective ranges

S.N.	Output Parameters	Range
1	Burden Rock Velocity (BRV)	6.75-11.73 m/s

Data Preprocessing: Data preprocessing is one of the crucial steps before predictive modeling. It involves feature selection and systematic data preparation to ensure robust model performance. The dataset is processed for the following preprocessing steps:

1. **Data normalization**: Features were normalized to ensure uniform scaling, reducing bias during training.
2. **Train-test split**: The dataset was divided into training and testing subsets, with 80% allocated for training and 20% for testing. This split ensures sufficient data for model training while preserving data for unbiased evaluation.

Neural network architectures: The study explores four distinct neural network architectures, each designed to capture varying levels of data complexity. These architectures were implemented using a sequential model approach, with differing numbers of hidden layers and neurons. Table 4 summarizes the proposed neural network models with their architectures. Every neural network architecture differs based on hidden layers, activation functions and optimizers used for neural network models. Activation functions play an important role in defining the architecture of the model. Some of them are discussed as follows:

The Rectified Linear Unit (ReLU) is considered one of the most effective activation functions in deep learning due to its simplicity and computational efficiency. ReLU outputs zero for negative inputs and passes positive inputs unchanged, introducing non-linearity without excessive computational overhead. Unlike sigmoid or tanh functions, ReLU mitigates the vanishing gradient problem, enabling faster training and better performance in deep networks[10]. Additionally, the sparsity introduced by ReLU activates only a subset of neurons, improving model efficiency and reducing the risk of overfitting.

The Adam optimizer (Adaptive Moment Estimation) is a widely used optimization algorithm that combines the advantages of momentum-based methods and adaptive learning rates. It calculates parameter-specific learning rates using the first and second moments of gradients, making it robust to noisy data, effective for large-scale problems[13]. Adam is known for its fast convergence and minimal need for hyperparameter tuning, making it a default choice in many deep learning tasks, especially where gradients are sparse, or objectives are non-stationary.

On the other hand, Stochastic Gradient Descent (SGD) updates model parameters using small batches or individual data samples, introducing randomness that allows the optimizer to escape local minima and to explore the solution space more effectively. Although SGD converges more slowly than adaptive methods like Adam, it often generalizes better for tasks such as image classification when paired with techniques like momentum or learning rate scheduling[5]. Both Adam and SGD are foundational optimization algorithms, each with distinct strengths that make them suitable for different applications in machine learning.

Table 4
Summary of neural network architectures for various models against various hyperparameters.

Model	Hidden Layers	Neurons Per Layer	Activation Function	Optimizer	Loss Function
Deep Multi-Layer Perceptron (Deep MLP)	4	128, 64, 32, 16	ReLU	Adam	Mean Squared Error
Deep Neural Network (DNN)	3	128, 64, 32	ReLU	Adam	Mean Squared Error
Simple Multi-Layer Perceptron (Simple MLP)	2	64, 32	ReLU	Adam	Mean Squared Error
Backpropagation Neural Network (BPNN)	2	64, 32	ReLU	SGD	Mean Squared Error

Training Parameters: To ensure a fair comparison, all models were trained using consistent parameters: Epochs 50 and Batch size 16. These parameters were selected to balance model learning and overfitting prevention.

Performance Evaluation Metrics: Model performance was comprehensively assessed using three key evaluation metrics: In all the equations, n is the number of data points, y_i is the ith actual value for the ith data point and $\hat{y}_i$ is the predicted value.

Mean Squared Error (MSE): MSE measures the average squared difference between predicted and actual values. Lower MSE values indicate better model performance. The formula for MSE is given by eq. 1:

$$MSE = (1/n)\ \Sigma\ (y_i - \hat{y}_i)^2 \qquad (1)$$

R-squared (Coefficient of Determination): R-squared evaluates the proportion of variance in the dependent variable explained by the model. It is calculated using eq. 2:|

$$R^2 = 1 - [\Sigma\ (y_i - \hat{y}_i)^2 / \Sigma\ (y_i - \bar{y})^2] \qquad (2)$$

R-squared offers insight into the proportion of variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1 with values closer to 1 indicating a better fit:

Mean Absolute Error (MAE): Mean absolute error (MAE) calculates the average absolute difference between predicted and actual values, providing a straightforward measure of prediction accuracy: It is expressed in eq. 3:

$$MAE = (1/n)\ \Sigma\ |y_i - \hat{y}_i| \qquad (3)$$

These metrics collectively provide a comprehensive assessment of model performance, enabling a nuanced comparison of the different neural network architectures.

Results and Discussion

The evaluation results are summarized in table 5 showing the performance of each model across the defined metrics. The results highlight the performance variability across the tested neural network models. The Backpropagation Neural Network (BPNN) emerged as the best-performing model, achieving the highest R^2 value of 0.821, the lowest MSE of 0.0995 and the lowest MAE of 0.2268. These results indicate that the BPNN effectively captured the underlying relationships in the dataset, demonstrating its suitability for this problem. The robust optimization technique (Stochastic Gradient Descent) and the relatively simpler architecture contributed to its strong generalization ability.

In contrast, the Simple Multi-Layer Perceptron (Simple MLP) performed poorly, with a negative R^2 value (-0.689). A negative R^2 indicates that the model's predictions were less accurate than using the mean of the target variable as a prediction. This suggests that the simple MLP suffered from underfitting, possibly due to its limited architecture with only two hidden layers, which may have been insufficient to capture the complexity of the data.

The Deep Neural Network (DNN) also delivered suboptimal results, with an R^2 of 0.599, an MSE of 0.222 and an MAE of 0.386. While better than the simple MLP, the DNN may have overfitted the training data due to its more complex architecture, reducing the ability to generalize to the test data. The Deep Multi-Layer Perceptron (Deep MLP) showed moderate performance with an R^2 of 0.742. Its relatively higher MSE (0.1437) and MAE (0.3089) suggest that while the model captured the data's complexity to some extent, it may have been prone to slight overfitting or struggled with optimization challenges.

Conclusion

The paradigm of predictive modeling of burden rock velocity in limestone mines helps to design blasts that achieve the desired fragmentation and enhance safer blasting operations by minimizing the risk of fly rock and excessive vibrations. Hence, a study was formulated to predict burden rock velocity using input parameters such as BH, CPD, TEC, SR, PF, JS and PL. The performance of the predictive models was evaluated based on the R-squared (R^2) score and other relevant metrics. Among the models tested, the backpropagation neural network model demonstrated the highest R^2 score, indicating a strong relationship between the predicted and actual values of burden rock velocity.

Table 5
Comparison of predictive models based on MSE, R² and MAE.

S.N.	NN Model	R²	MSE	MAE
1	Deep Multi-Layer Perceptron (MLP)	0.742	0.143	0.308
2	Deep Neural Network (DNN)	0.599	0.222	0.386
3	Simple Multi-Layer Perceptron (MLP)	-0.689	0.940	0.817
4	Backpropagation Neural Network (BPNN)	0.821	0.099	0.226

The R^2 score for the backpropagation neural network model was calculated to be $R^2 = 0.82$, suggesting that 82% of the variance in the burden rock velocity can be explained by the model. This high R^2 value correlates with improved prediction accuracy, as evidenced by a lower mean square error (MSE) of MSE = 0.099 and mean absolute error of MAE = 0.226. The accuracy of the prediction models can be enhanced by using more advanced hybrid models or stacked models by incorporating neural networks and ensemble methods.

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