

Article

Predicting Blast-Induced Area of Tunnel Face in Tunnel Excavations Using Multiple Regression Analysis and Artificial Intelligence

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Abstract

In underground construction, the drilling and blasting method is widely used due to its advantages, such as low cost, simple implementation, and applicability under various geological and hydrogeological conditions. One parameter that significantly affects the effectiveness of drilling and blasting is the post-blast tunnel cross-sectional area. In this study, multiple linear regression analysis (MLRA) and multiple nonlinear regression (MNLRA) models were used to predict the area of a tunnel face after blasting, utilizing 136 datasets containing parameters measured from the tunnel face area after blasting during the Deo Ca tunnel construction project. Three deep learning models, an artificial neural network (ANN) and two hybrid models combining an ANN with the particle swarm optimization (PSO) algorithm and an ANN with a genetic algorithm (GA), were then developed to predict the tunnel face area after blasting. The input variables for the calculation and prediction models included the designed tunnel face area (S_d), the specific charge (SC) of the explosion, the average borehole length (L), and the rock mass rating (RMR) of the rock mass on the tunnel face. The GA-ANN model's results, including determination coefficient (R^2) and mean square error (MSE) values of $R^2_{\text{train}} = 0.9562$, $R^2_{\text{testing}} = 0.94$, $\text{MSE}_{\text{training}} = 0.0156$, and $\text{MSE}_{\text{testing}} = 0.0302$, indicate that it provides a better prediction of the tunnel face area after blasting than the other models.

Keywords: area of tunnel face; multiple linear regression; multiple nonlinear regression; artificial intelligence; genetic algorithm (GA); particle swarm optimization (PSO)

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1. Introduction

Drilling and blasting is a key method in underground construction because it offers several benefits: low cost, simplicity, and adaptability to various geological conditions and tunnel cross-sectional shapes. However, overbreak and/or underbreak remain a key challenge in using this method (Figure 1). The post-blast tunnel cross-sectional area is a

key factor in evaluating the effectiveness of the drilling-blasting method. This area influences the amount of work required in a tunnel construction cycle, including the volume of earth and rock to be excavated, the volume of tunnel lining to be installed, and the amount of ventilation and energy needed. This relationship has been studied and confirmed by researchers in several publications, including [1–3]. However, predicting the area of the tunnel face after blasting remains challenging.

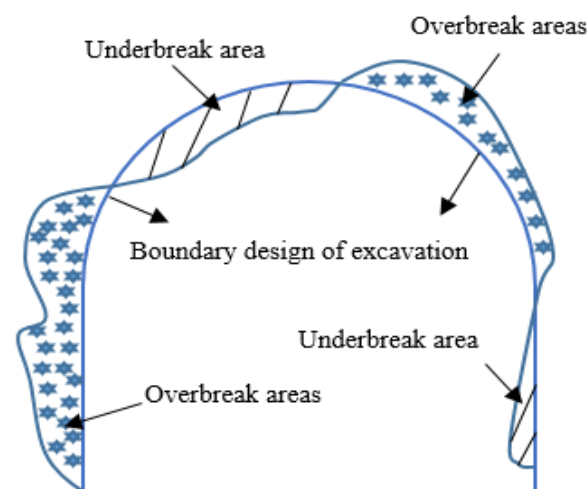


Figure 1. The tunnel cross-section after blasting.

The post-blast tunnel cross-sectional area depends on several factors, including geological conditions, drilling and blasting patterns, and the shape of the tunnel cross-section, or a combination. These factors can be divided into two groups. The first consists of controllable factors, such as blasting parameters and the shape of the tunnel cross-section. The second group includes non-controllable factors, such as the geological and hydrogeological conditions of the rock mass surrounding the tunnel. Some researchers consider the shape of the tunnel cross-section to be part of a third group of semi-controllable factors. Several studies indicate that uncontrollable factors, such as geological conditions and hydrogeology, significantly influence the tunnel face area after blasting. Chakraborty et al. [4], and Murthy et al. [5], have noted that blasting efficiency depends on uncontrollable parameters. Innaurato et al. [6], demonstrated the influence of one important uncontrollable parameter, the rock mass rating (*RMR*), on the efficiency of drilling and blasting. The impact of uncontrollable parameters, including *RMR* and the shape of the tunnel cross-section, has also been studied and highlighted in publications by Ibarra et al. [7], and Mandal et al. [8]. Singh et al. [9], described the causes and impact of overbreak in underground excavations, and Shiwei et al. [10] pointed out the influence of the fracture system and geological conditions on the outcome of drilling and blasting during tunnel construction. Using artificial intelligence, Mottahedi et al. [11]; Monjezi et al. [12]; Khandelwal et al. [13]; and Monjezi et al. [14], have published important research on how uncontrollable parameters affect the tunnel face area after drilling and blasting (Table 1).

Table 1. Artificial intelligence models used to predict blast-induced parameters.

Number	Authors	Areas of Study	Models Used
1	Monjezi et al. [12]	Evaluating of blasting pattern's influence on back break	ANN
2	Khandelwal et al. [13]	Prediction of ground vibration caused by blasting	SVM
3	Monjezi et al. [14]	Backbreak prediction in open-pit blasting	Fuzzy
4	Rezaei et al. [15]	Prediction of flyrock in surface mining	Fuzzy

5	Jang and Topal. [2,16]	Prediction of overbreak in tunnel blasting	LMRA, NMRA, and ANN
6	Bazzazi A. et al. [17]	Prediction of backbreak in open-pit blasting	ANN and ANFIS
7	Ghasemi et al. [18]	Prediction of peak particle velocity	ANFIS-PSO
8	Armaghani D.J. et al. [19]	Developing a hybrid PSO-ANN model for estimating ultimate bearing capacity of rock-socketed piles	PSO-ANN
9	Mohamad E. et al. [20]	Estimating air overpressure from blasting operations	ANN and GA-ANN
10	Hasanipanah et al. [21]	Prediction of blast-induced ground vibration	PSO
11	Hasanipanah et al. [22]	Estimation of blast-induced ground vibration	ANN and GA
12	Mohammadi H et al. [23]	Prediction of blast-induced overbreak	LMRA
13	Chen, X.L et al. [24]	Prediction of shear strength for squat RC walls using a hybrid ANN-PSO model.	ANN and PSO
14	Mottahedi A. et al. [25]	Overbreak prediction in underground excavations	ANFIS and PSO
15	Nguyen H. et al. [26]	Predicting blast-induced peak particle velocity using BGAMs, ANN, and SVM: case study at Nui Beo open-pit coal mine in Vietnam	BGAMs, ANN, and SVM
16	Liu, Y., Hou, S. [27]	Rockburst prediction based on particle swarm optimization and machine learning algorithm	ANN-GA
17	Roy, D.H., Singh, T.N. [28]	Predicting deformational properties of Indian coal: soft computing and regression analysis approach	ANN and ANFIS
18	Shang, Y. et al. [29]	Novel artificial intelligence approach to predicting blast-induced ground vibration in open-pit mines	ANN, SVM, and KNN
19	Chi T.N. et al. [30]	Prediction of blast-induced area of tunnel face in underground excavations	ANN and ANFIS

Controllable parameters can be adjusted to achieve a desired tunnel face area after blasting. These parameters include the specific charge (SC) of the explosion, average bore-hole length (L), designed tunnel face area (S_d), delay timing (D_t), and the shape of the tunnel cross-section (Rustan [31]; Germain and Hadjigeorgiou. [32]; Imashev, A et al. [33]; Mahtab et al. [34]; Maerz et al. [35]; Konya and Walter. [36]). In addition to statistical methods for predicting tunnel overbreak or underbreak (Mohammadi M et al. [37]; Mohamad E.T et al. [38]), some methods use artificial intelligence, such as artificial neural networks (ANNs), to predict overbreak or underbreak when drilling and blasting is used for tunnel construction. However, ANN models have disadvantages, including a slow learning rate and the potential to become trapped in local minima (Hajihassani et al. [39]; Bassar, H. et al. [40]). To make these predictive models more accurate, scientists have used optimization algorithms such as particle swarm optimization (PSO) and genetic algorithms (GAs). Table 1 provides examples of artificial intelligence models used to predict parameters when using the blasting method. In 2022, Chi T.N. et al. [30] developed an AI model utilizing artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) to predict the area of a tunnel face after blasting. Their study achieved positive results. However, the research did not compare the performance of these deep learning models with that of multiple linear regression analysis (MLRA) and multiple nonlinear regression analysis (MNLR) models for this specific prediction task.

There is a lack of published research on highly accurate models combining linear methods with artificial intelligence to predict the tunnel face area after blasting. Existing studies in this field have primarily focused on predicting the overbreak or underbreak coefficient of the tunnel face after blasting, rather than the tunnel face area itself. Developing such a model for accurate prediction and calculation will assist designers and constructors working on underground projects that use drilling and blasting, resulting in im-

proved work efficiency, minimized construction risks (rockfall and significant rock deformation surrounding the tunnel, accompanied by substantial alterations in the surrounding rock environment's properties), and reduced cost. The tunnel face area after blasting is a critical parameter that determines the workload for each construction cycle in these projects (this includes excavation, support structures, ventilation, and energy supply). As a result, the construction progress of underground projects using drilling and blasting methods will be accelerated. In this study, multiple linear regression analysis (MLRA) and multiple nonlinear regression analysis (MNLR) models were used to predict the tunnel face area after blasting. Additionally, hybrid models were developed using an artificial neural network (ANN) combined with optimization algorithms, the genetic algorithm (GA) and the particle swarm optimization (PSO) algorithm, to determine the tunnel face area after blasting. The results demonstrate the advantage of artificial intelligence in determining and predicting the tunnel face area after blasting, considering the influence of both non-controllable parameters, such as the rock mass rating (*RMR*), and controllable parameters, such as the designed tunnel face area (S_d), specific charge (*SC*), and average borehole length (*L*). This is especially true when the ANN model is optimized using the GA and PSO algorithms.

2. Methodology of the Study

2.1. Case Study and Data

Located between Phu Yen and Khanh Hoa Provinces, the Deo Ca road tunnel project (Figure 2) consists of two parallel tunnels, each approximately 4.1 km long. The project site has complex geological conditions and is primarily composed of igneous and metamorphic rock. The rock mass rating (*RMR*) ranges from 5 to 74. Areas with crumpled, metamorphic, and heavily weathered rock have a low rock mass rating (*RMR* between 5 and 35), while stable, hard rock areas have a higher rock mass rating (*RMR* between 55 and 74).

We collected 136 datasets for input data, each including four input parameters: the rock mass rating (*RMR*), designed tunnel face area (S_d), average borehole length (*L*), and the specific charge (*SC*) of the explosion. We used 109 datasets (80%) to train the models and 27 datasets (20%) for testing. The output data represent the tunnel face area after blasting (*SA*). It is important to note that the designed tunnel face area (S_d), average borehole length (*L*), and specific charge (*SC*) are considered controllable parameters. The rock mass rating (*RMR*), however, is classified as a non-controllable parameter. In practice, the tunnel face area after blasting (*SA*) is typically measured using two methods: traditional manual measurement with tapes or rulers, and radar scanning to identify the boundary points of the tunnel face, which are then used to calculate the area. The values for all parameters are shown in Table 2. The predictive models in this study are limited by the scope of the data used to develop them. This is a constraint. To address this, research from Zhibin Guo et al. [41,42] could be included to broaden the data and create a more general predictive model. This is the next direction for this study.

Table 2. Model parameter ranges and mean values.

Parameter	Symbol	Unit	Category	Min	Max	Mean	Std. Deviation
Average borehole length	L	m	Input	1.0	3.2	1.9569	0.6691
Designed tunnel face area	S_d	m ²	Input	49.26	64.855	54.6973	6.1486
Specific charge	SC	kg/m ³	Input	0.32	2.54	1.4092	0.4608
Rock mass rating	<i>RMR</i>	-	Input	5.0	74.0	49.7982	17.1133
Tunnel face area after blasting	SA	m ²	Output	50.276	71.049	59.0051	6.3834



Figure 2. Deo Ca tunnel.

2.2. Multiple Linear Regression Analysis (MLRA) Model

Multiple linear regression analysis is a statistical technique used to model the relationship between a dependent variable and two or more independent variables. In this method, the variability of the dependent variable is explained by the independent variables included in the model, and the model's parameters are estimated using data from these variables. In this technical analysis, multiple linear regression analysis (MLRA) is employed to quantify the coefficients that characterize the interactions between independent predictors and the dependent variable (Gokceoglu and Zorlu, [43]). In multiple linear regression analysis, this relationship can be expressed as an equation:

$$Y = \alpha_0 X_0 + \alpha_1 X_1 + \alpha_3 X_3 + \dots + \alpha_n X_n + \Delta \quad (1)$$

where Y is the dependent variable, X_i represents the independent variables, α_i represents the partial regression coefficients, Δ is a constant and Δ is the intercept or error, and n is the number of observations.

Multiple linear regression analysis has been used in numerous studies to predict drilling and blasting parameters in underground construction [2,16,23].

Using SPSS IBM 2022 software, multiple linear regression analysis was applied to reveal the correlation between the resultant post-blast tunnel face area (S_A) and its influencing factors is examined in this study. These independent variables included the rock mass rating (RMR), designed tunnel face area (S_d), specific charge (SC), and average bore-hole length (L):

$$S_A = 3.997 - 0.355 \times L + 1.018 \times S_d - 0.248 \times SC + 0.07 \times RMR \quad (2)$$

Whether a multiple regression equation effectively represents the data is commonly determined by R^2 values, which fall within the 0 to 1 interval. Accuracy is considered satisfactory in this discipline when R^2 reaches at least 0.5; otherwise, the resulting model may lack reliability. Subsequent to R^2 assessment, we conducted rigorous testing for multicollinearity and autocorrelation. The high R^2_{training} value of 0.9154 obtained during the training phase demonstrates the robustness of our proposed model. In the testing datasets, the coefficient of determination was $R^2_{\text{testing}} = 0.9113$ (Figure 3).

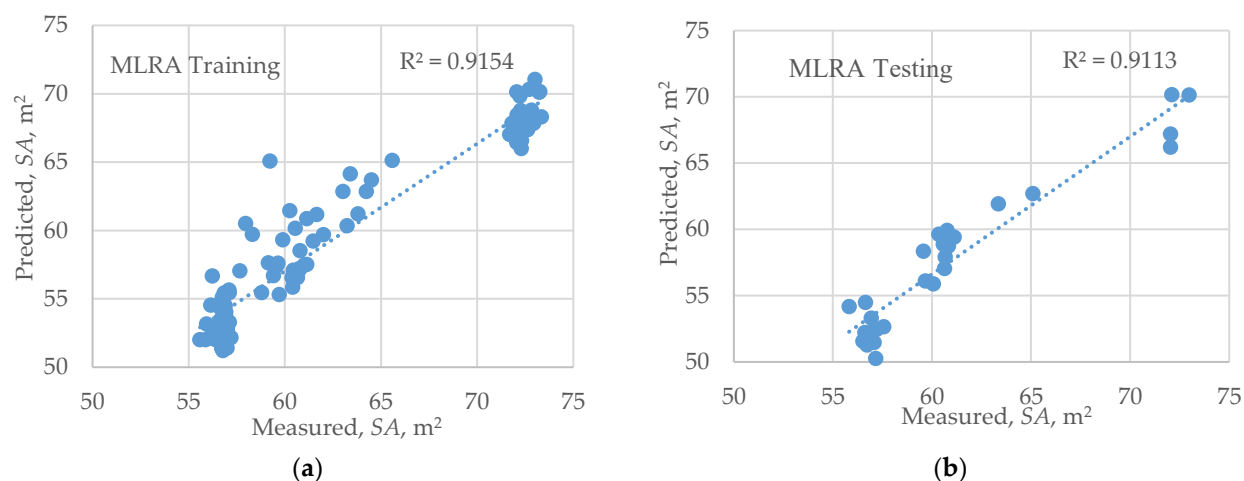


Figure 3. The tunnel face area after blasting (SA) was measured and predicted using the MLRA model: (a) with training datasets; (b) with testing datasets.

We used the Durbin–Watson statistic to assess autocorrelation among the residuals of our linear regression. The Durbin–Watson statistic has a value between 0 and 4. (Mohammadi H et al. [23]). In this study, the Durbin–Watson value was 2.089, satisfying the requirement. The sign index, another indicator of interest, was also examined to assess the correlation between independent and dependent variables. A sign index greater than 5% suggests a weak or nonexistent correlation between the variables under consideration. Multicollinearity was checked using the variance inflation factor (VIF). Typically, a VIF greater than 10 for an independent variable indicates multicollinearity (Neter et al. [44]; Bui et al. [45]). In this situation, the variable might not adequately explain the changes in the dependent variable within the regression model. In this study, all these parameters were carefully checked and found to be within acceptable limits. If any variable’s index falls outside the acceptable limits, that variable should be removed from the regression model being constructed (Jang and Topal. [2]).

Table 3 presents the parameter values for the MLRA model, displaying the input variables and their corresponding coefficients in the final model. To determine statistical significance, each variable’s observed significance was tested. A variable is considered statistically significant if its observed significance level is less than the predetermined significance level. The “null hypothesis”, as defined by Craparo [46], states that no relationship exists between two measured variables. Following Fisher [47], a variable is considered highly statistically significant if its significance level (probability value) is less than 0.01. Significance levels between 0.01 and 0.05 indicate statistical significance. Higher significance levels warrant careful attention to the variable’s statistical power.

Table 3. Coefficient values in the MLRA model.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
Constant	3.997	1.406		2.842	0.05		
Average borehole length (L)	−0.355	0.383	−0.037	−0.926	0.356	0.365	2.739
Designed tunnel face area (S_d)	1.018	0.27	0.981	37.618	0.000	0.867	1.154
Specific charge (SC)	−0.248	0.624	−0.018	−0.398	0.691	0.291	3.442
Rock mass rating (RMR)	0.07	0.020	0.020	0.371	0.711	0.205	4.869

2.3. Multiple Nonlinear Regression (MNL) Model

Multiple linear regression analysis is less accurate when predicting the cross-sectional area after blasting, likely because the model includes many input variables and the input data and output data (the tunnel face area after blasting) are not linearly related. A multiple nonlinear regression (MNL) model can be employed to address this issue. Indeed, most relationships between the input variables (independent variables) and output variables (dependent variables) in the model are nonlinear. Multiple nonlinear regression can improve the accuracy and usability of the overall model. Building an MNL model requires determining the individual nonlinear regression relationship between each input variable and the output variable. Then, the appropriate nonlinear functions for each independent variable can be selected based on the results of these individual nonlinear regression models. This results in the construction of a comprehensive multiple nonlinear regression model relating all input variables to the output variable. Table 4 presents statistics on the coefficients of determination (R^2) and mean squared error (MSE) for each input variable's individual nonlinear regression model with the output variable. Regarding the prediction of blast-induced tunnel face area using the multiple nonlinear regression (MNL) model, each univariate nonlinear component was individually investigated and formulated. These components were subsequently integrated into a comprehensive multivariate model to enhance the precision of post-blast area calculations and predictions.

Table 4. The coefficients of determination of the appropriate multiple nonlinear regression models relating each independent variable and the dependent variable.

Input Variables	R^2 of Equations								
	Linars	Logarithmic	Quadratic	Cubic	Compound	Power	Inverse	Exponential	S
Average borehole length (L)	0.105	0.061	0.312	0.360	0.092	0.051	0.028	0.092	0.021
Designed tunnel face area (S_d)	0.938	0.940	0.941	0.941	0.928	0.935	0.941	0.930	0.938
Specific charge (SC)	0.046	0.02	0.093	0.119	0.04	0.016	0.004	0.04	0.002
Rock mass rating (RMR)	0.067	0.011	0.420	0.540	0.056	0.007	0.00	0.038	0.00

By combining the individual nonlinear regression models that relate each independent variable to the dependent variable, we derive an overall multiple nonlinear regression model for all independent variables, as follows:

$$S_A = 119.512 - 11.875 \times L + 4.553 \times L^2 - 0.494 \times L^3 - \frac{3006.218}{S_d} + 7.858 \times SC - 6.527 \times SC^2 + 1.620 \times SC^3 - 0.017 \times RMR \quad (3)$$

Figures 3 and 4 show the predicted tunnel face area after blasting, as determined by the MLRA and MNL models for both the training and testing datasets. For the training datasets, $R^2_{\text{training}} = 0.9357$, and for the testing datasets, $R^2_{\text{testing}} = 0.8995$.

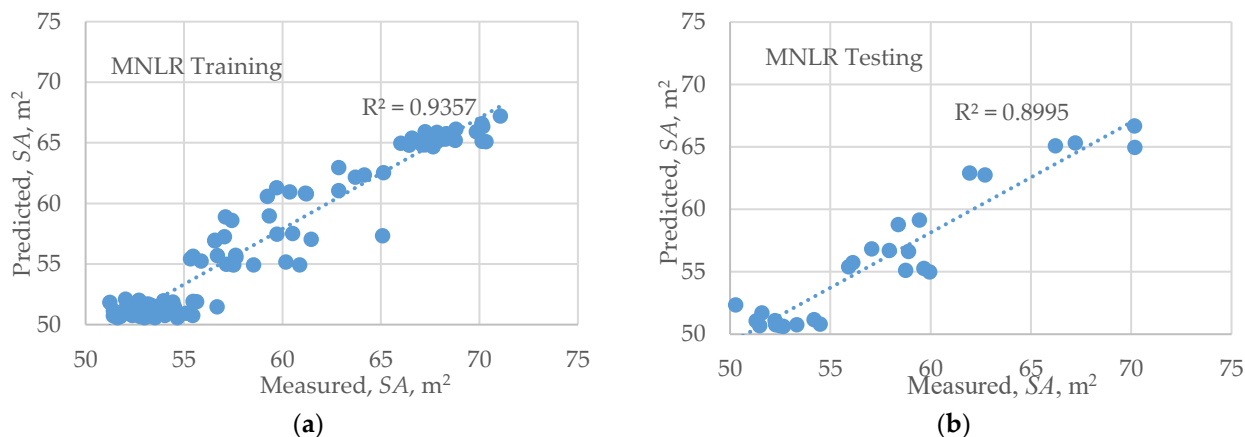


Figure 4. Measured and predicted values of tunnel face area after blasting (SA) obtained via the MNLR model: (a) training datasets; (b) testing datasets.

2.4. Artificial Neural Network (ANN) Model

An artificial neural network (ANN) is a simplified mathematical model that mimics the human brain's functioning, hence the name. ANNs can model complex relationships between input variables to simulate one or more output variables (Specht [48]). A specific ANN model is defined by key components such as its transfer function, structure, and learning rules (Simpson [49]). The performance and accuracy of an ANN depend on defining an initial set of weights and specifying how these weights are adjusted during training to improve accuracy (Yilmaz, I et al. [50]). We propose using a single hidden layer of neurons and employing the back-propagation (BP) algorithm within the neuron model. Training a neural network using the BP algorithm involves two main steps across different layers: forward propagation and backward propagation. In forward propagation, the input signal is applied to the network's nodes, and its effect moves through each layer, ultimately generating an output as the network's actual response (Figure 5). If this response deviates from the desired value, error correction is performed to adjust the weights and biases within the network to minimize error.

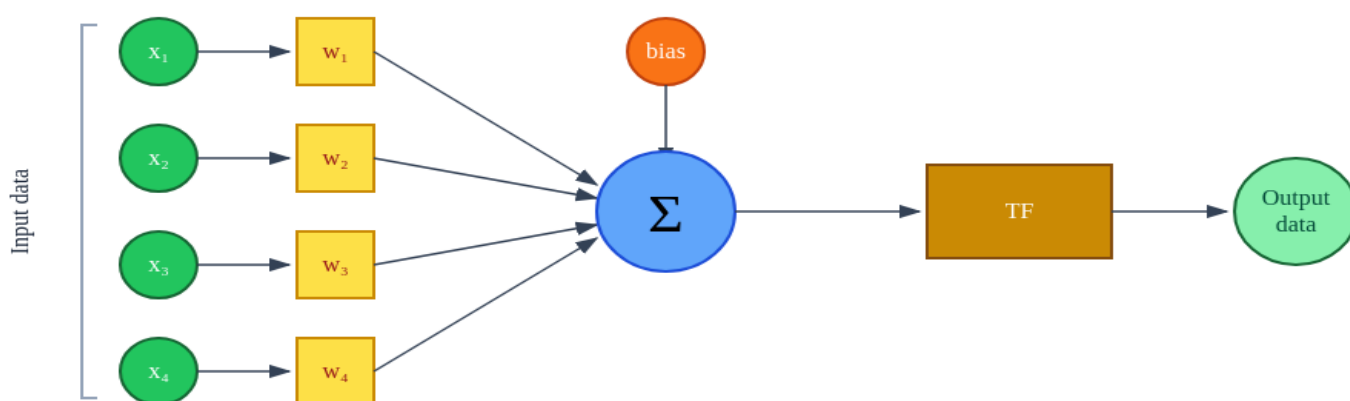


Figure 5. Diagram of the artificial neural network (ANN) used in the study.

In the backpropagation (BP) algorithm, input data are fed into the input layer and propagate through the network to produce an output. Each neuron calculates its weighted input using the following equation (Yilmaz, I et al. [50]):

$$X = \sum_{i=1}^n x_i \times w_i - \beta \quad (4)$$

where X represents the output data at the output layer of the artificial neural network, x_i is the value of the i^{th} input, w_i is the weight of the i^{th} input, n is the quantity of input data, and β is the threshold applied to the neuron that is processing the data.

To develop an artificial neural network (ANN) for predicting the area of a tunnel face after blasting with four input parameters, the rock mass rating (RMR), designed tunnel face area (S_d), average borehole length (L), and the specific charge (SC) of the explosion, the data used to train and test the ANN model must be processed (Figure 6). Because the transfer function in the ANN model is the TANSIG function, the data need to be normalized to the interval $[-1, 1]$, using to the following equation (Armaghani D.J et al. [51]):

$$X_n = \frac{(X - X_{\min})}{(X_{\max} - X_{\min})} \times 2 - 1 \quad (5)$$

where X_n is the normalized value of the variable, X is the initial value of the variable, $X_{\max}$ is the initial maximum value of the unnormalized variable, and $X_{\min}$ is the initial minimum value of the unnormalized variable.

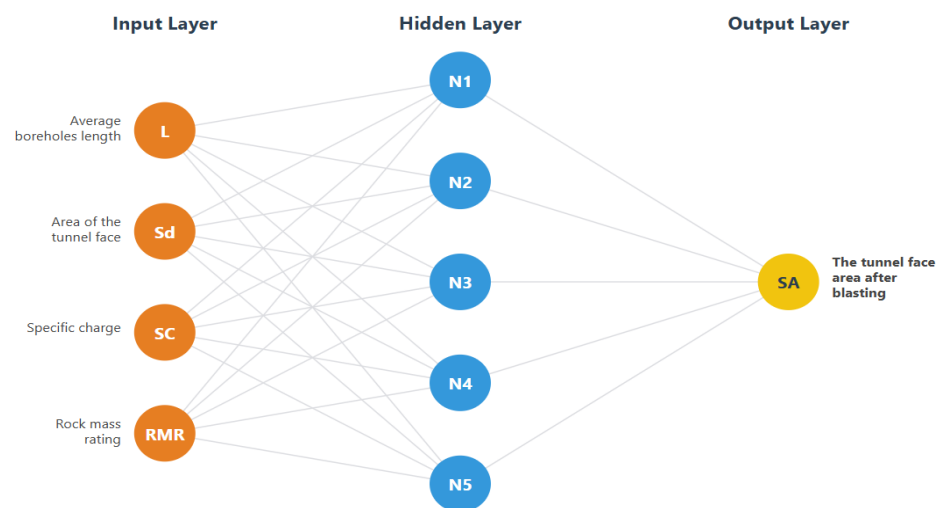


Figure 6. Artificial neural network (ANN) structure.

One of the main challenges in using artificial neural networks (ANNs) is determining the optimal network architecture, specifically the number of hidden layers and the appropriate number of neurons within those layers. This optimization is crucial for obtaining the most accurate results from the ANN (Simpson P.K [49]). Many studies have successfully employed the Levenberg–Marquardt backpropagation training algorithm in ANNs (Basheer I et al. [52]). Research suggests that ANNs with a single hidden layer can approximate any continuous function (Motahari, M et al. [53]). Furthermore, using a single hidden layer in an ANN can simplify the model, reduce processing time, and mitigate overfitting. Therefore, we employed an ANN using a single hidden layer. Researchers have suggested different formulas to calculate the best number of neurons for the hidden layer. Table 5 provides several formulas that can be used to estimate a suitable number of neurons for the hidden layer of an ANN model.

Table 5. Determining a suitable number of neurons for the hidden layer of the ANN model.

Heuristic	Reference
$\leq 2 \times N_i + 1$	Hecht-Nielsen [54]
$\frac{(N_i + N_0)}{2}$	Ripley [55]
$\frac{2 + N_0 \times N_i + 0.5 \times N_0 \times (N_0^2 + N_i) - 3}{N_i + N_0}$	Paola [56]
$\frac{2 \times N_i}{3}$	Wang [57]
$\sqrt{N_i \times N_0}$	Masters [58]
$2 \times N_i$	Kaasra and Boyd [59]

In the above equations, N_i is the number of neurons in the input layer (number of input neuron), and N_0 is the number of neurons in the output layer.

To determine the appropriate number of neurons for the hidden layer of the artificial neural network (ANN) model, we built several models, each with a different number of neurons in the hidden layer. We then evaluated each model using training and testing datasets, based on its coefficient of determination (R^2) and mean squared error (MSE). The models with higher R^2 values and lower MSE values were considered more suitable. Each model evaluation was performed five times to ensure reliable results.

The mean square error (MSE) was calculated using the following equation [49]:

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - y'_i)^2 \quad (6)$$

The coefficient of determination R^2 was calculated using the following equation [49]:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^N (y_i - y'_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \right]^2 \quad (7)$$

where N is the quantity of data at the input layer, y_i is the i^{th} actual measured value, y'_i is the i^{th} predicted value, $\bar{y}$ is the actual measured mean.

Based on the results in Tables 6 and 7, as well as the average R^2 and MSE values for both the training and testing datasets of the ANN model, shown in Figures 7 and 8, the number of hidden nodes in the artificial neural network (ANN) was determined. A reasonable ANN model with the optimal architecture ($4 \times 5 \times 1$) was chosen, consisting of four neurons in the input layer, five neurons in the hidden layer, and one neuron in the output layer. This model architecture was expected to yield the highest accuracy.

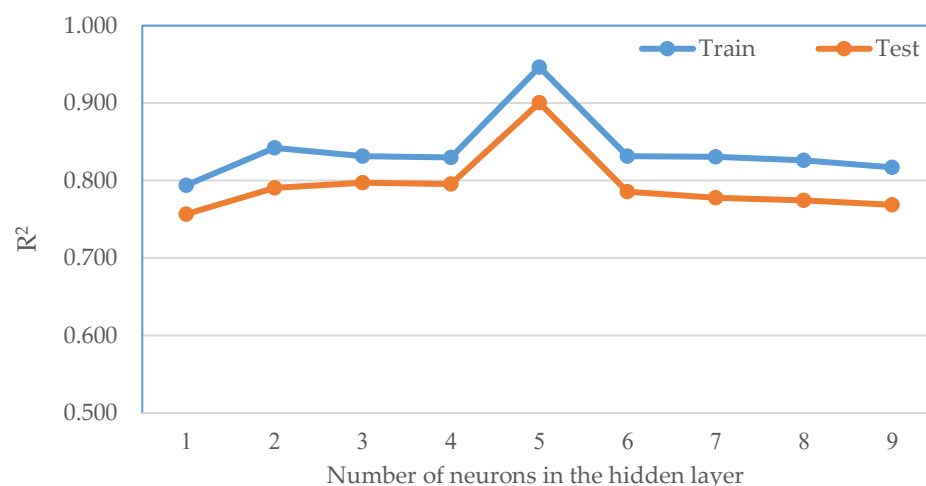


Figure 7. The relationship between the coefficient of determination (R^2) and the number of neurons in the hidden layer of an artificial neural network (ANN) model.

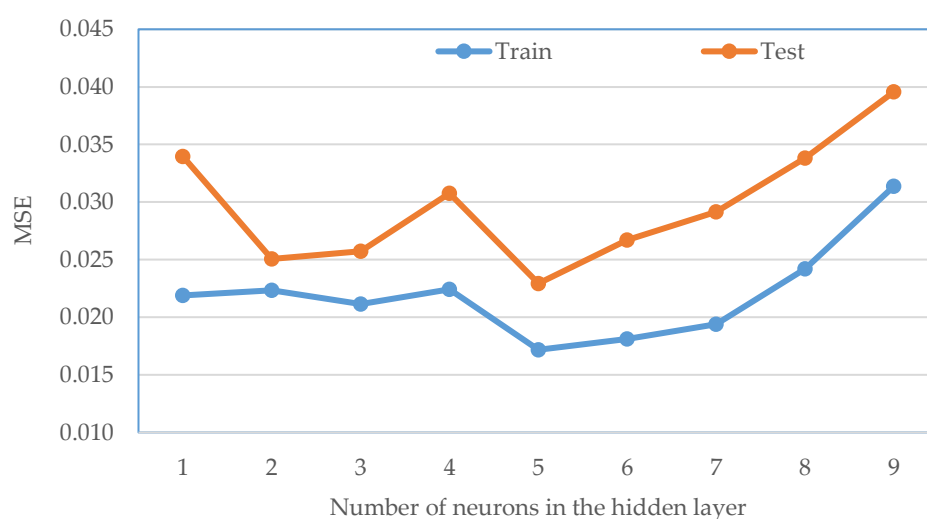


Figure 8. The relationship between the mean squared error (MSE) and the number of neurons in the hidden layer of an artificial neural network (ANN) model.

Table 6. Coefficient of determination (R^2) results for various artificial neural network (ANN) models with different numbers of hidden nodes.

Model	Number of Neurons in the Hidden Layer	Model Results											
		R^2											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
1	1	0.756	0.769	0.952	0.791	0.774	0.723	0.753	0.760	0.734	0.739	0.794	0.756
2	2	0.939	0.771	0.934	0.762	0.754	0.777	0.822	0.740	0.762	0.900	0.842	0.791
3	3	0.939	0.758	0.921	0.740	0.771	0.769	0.760	0.756	0.763	0.962	0.831	0.797
4	4	0.933	0.755	0.951	0.762	0.757	0.759	0.757	0.735	0.750	0.965	0.829	0.795
5	5	0.948	0.901	0.935	0.842	0.949	0.919	0.952	0.909	0.948	0.929	0.946	0.901
6	6	0.937	0.768	0.952	0.687	0.764	0.778	0.757	0.725	0.746	0.968	0.831	0.785
7	7	0.933	0.721	0.924	0.766	0.757	0.779	0.770	0.748	0.768	0.875	0.830	0.777
8	8	0.933	0.736	0.927	0.759	0.743	0.741	0.761	0.733	0.765	0.901	0.826	0.774
9	9	0.932	0.725	0.944	0.750	0.742	0.711	0.743	0.729	0.723	0.926	0.817	0.768

Table 7. Mean squared error (MSE) results for several artificial neural network (ANN) models with varying numbers of hidden nodes.

Model Number	Number of Neurons in the Hidden layer	Model Results											
		MSE											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Train-ing	Test-ing	Train-ing	Test-ing	Train-ing	Test-ing	Train-ing	Test-ing	Train-ing	Test-ing	Train-ing	Test-ing
1	1	0.02180	0.02480	0.01829	0.06117	0.01524	0.03576	0.02168	0.02413	0.03246	0.02390	0.02189	0.03395
2	2	0.02210	0.02910	0.02390	0.02194	0.02232	0.01779	0.02344	0.01806	0.01999	0.03839	0.02235	0.02506
3	3	0.02210	0.03470	0.02771	0.02962	0.01652	0.01867	0.02069	0.01834	0.01864	0.02726	0.02113	0.02572
4	4	0.02420	0.04490	0.01922	0.02173	0.02006	0.02238	0.02552	0.03844	0.02306	0.02638	0.02241	0.03077
5	5	0.01970	0.03380	0.02350	0.0595	0.01876	0.02838	0.01678	0.04633	0.00201	0.02241	0.01718	0.02294
6	6	0.02430	0.03020	0.01746	0.04356	0.01809	0.01841	0.01859	0.03124	0.01213	0.01016	0.01811	0.02671
7	7	0.01960	0.03050	0.01898	0.01785	0.02835	0.01669	0.01831	0.03385	0.01178	0.04692	0.01940	0.02916
8	8	0.02907	0.02010	0.02528	0.03684	0.03034	0.05216	0.01898	0.04617	0.01740	0.01383	0.02421	0.03382
9	9	0.02930	0.03270	0.02195	0.03742	0.03767	0.04872	0.02837	0.04029	0.03957	0.03871	0.03137	0.03957

Figures 9–11 and Table 8 indicate a strong positive correlation between the measured tunnel face area after blasting and the area predicted by the MLRA, MNLR, and artificial neural network (ANN) models. Examining the coefficients of determination (R^2) for the MLRA, MNLR, and ANN models for both the training and testing datasets and summing the R^2 values for each model reveals that the ANN model has the highest coefficient of determination for both datasets. Comparing the accuracy of the MLRA, MNLR, and ANN models' predictions of the tunnel face area after blasting with actual data from the Deo Ca tunnel construction project (Figures 9 and 10) reveals that the ANN model can predict and calculate the tunnel face area after blasting with high accuracy. The research findings presented in this paper indicate that the ANN model outperforms MLRA and MNLR models.

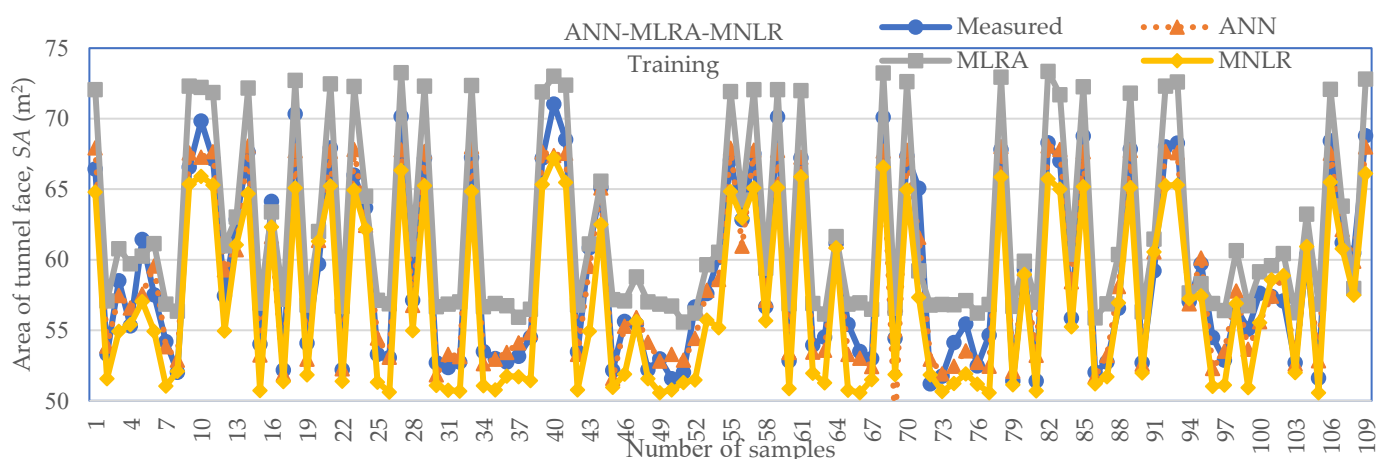


Figure 9. Comparing the measured and predicted tunnel face area after blasting (SA) using various training datasets.

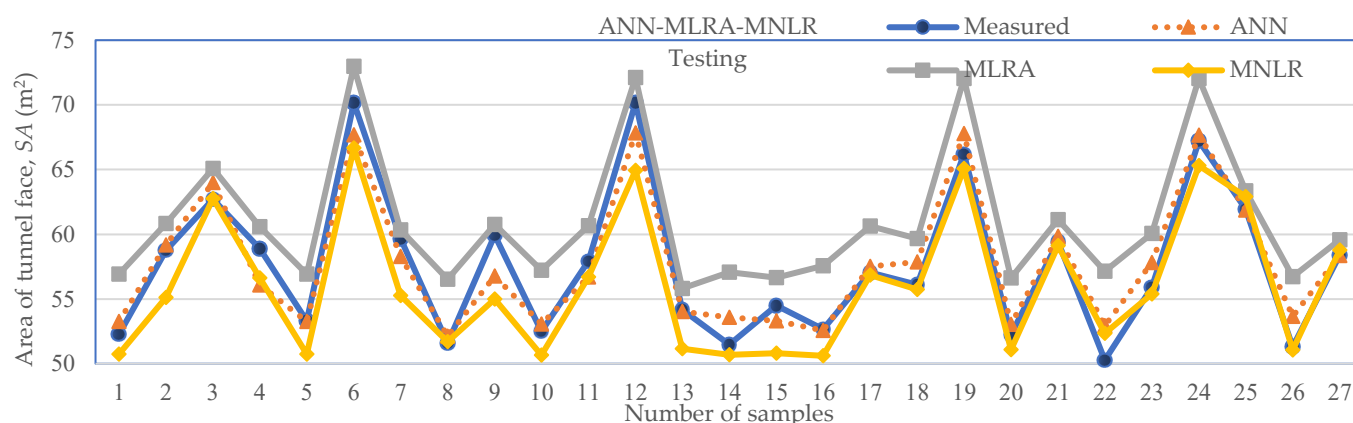


Figure 10. Comparing the measured and predicted tunnel face area after blasting (SA) using various testing datasets.

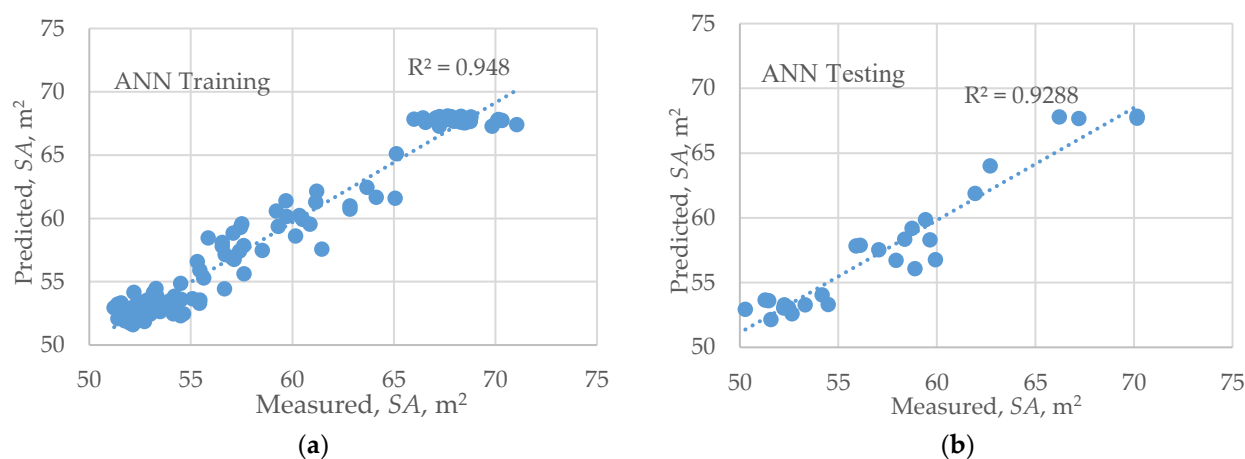


Figure 11. Measured and predicted area of tunnel face (SA) obtained via ANN model: (a) training datasets; (b) testing datasets.

Table 8. The coefficient of determination (R^2) and total rank values obtained from the MLRA, MNRA, and ANN predictive models.

Model	R^2				Total Rank
	Training	Rank	Testing	Rank	
MLRA	0.915	1	0.911	2	3
MNLR	0.935	2	0.899	1	3
ANN	0.948	3	0.928	3	6

2.5. The Hybrid GA-ANN Model

2.5.1. Contents of the Genetic Algorithm (GA)

Holland's groundbreaking research on the genetic algorithm (GA) was published in 1975 [60]. A key advantage of the genetic algorithm (GA) is its ability to address intricate, nonlinear problems. The approach used in this study combines a genetic algorithm (GA) with an artificial neural network (ANN) model to develop a hybrid model (Figure 12). This hybrid approach is designed to handle complex nonlinear problems in underground construction, specifically the calculation and prediction of the tunnel face area after blasting. The hybrid GA-ANN model addresses the shortcomings of using an artificial neural network (ANN) on its own to predict the tunnel face area after blasting, improving accuracy by enhancing model convergence. Our results show that the hybrid GA-ANN model [61], which combines a genetic optimization algorithm with an artificial neural network,

produces highly accurate predictions of the tunnel face area after blasting. The model's results achieved high convergence, as evidenced by its coefficient of determination R^2 and mean squared error MSE. When implementing the genetic algorithm (GA), careful selection of design parameters for each model is crucial, as these parameters significantly impact the algorithm's convergence and the model's overall results.

Genetic Algorithm (GA)

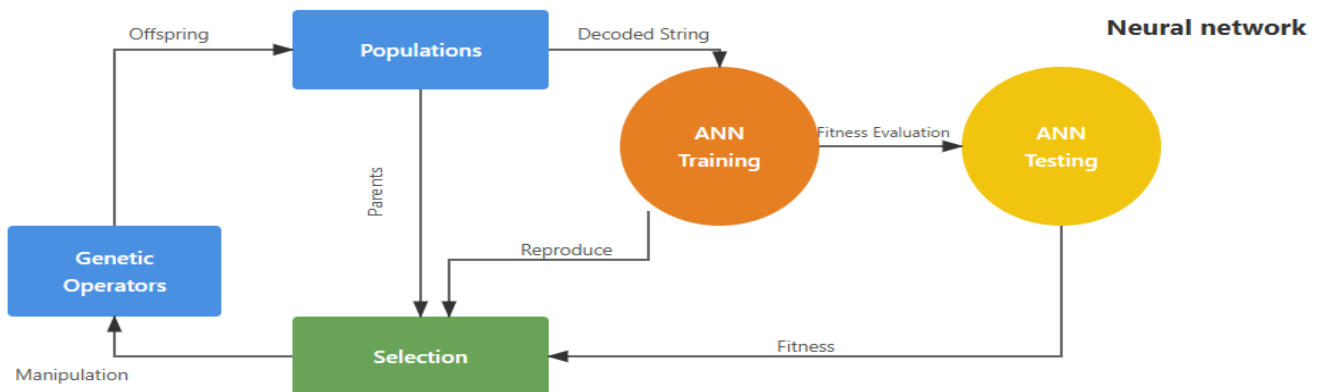


Figure 12. Flow chart of hybrid GA-ANN model's logic [19].

In the hybrid GA-ANN model, the weight w is optimized as the artificial neural network (ANN) processes information through neurons in its layers. The connection weights are updated repeatedly across iterations until the model converges, reaching an acceptable error level or the specified training tolerance at the ANN's output layer. In this study, the initial 136 datasets were divided into two parts: a training set comprising 80% of the data (109 randomly selected datasets) and a testing set comprising the remaining 20% (27 randomly selected datasets). The evaluation process followed a trial-and-error framework, employing the K-fold cross-validation technique as proposed by Diamantidis et al. [62]. The dataset was partitioned into K folds; K-1 folds were allocated for model training, while the remaining fold was executed as the test set to determine the model's accuracy. These datasets were used to determine the necessary parameters for the hybrid GA-ANN model. The data in both the training and testing sets were randomly selected from the original dataset for training and testing the hybrid GA-ANN model.

2.5.2. The Parameters of the GA-ANN Hybrid Model

To determine the best settings for the hybrid GA-ANN model, population sizes from 25 to 600 were tested. Previous research found that 500 iterations helped hybrid GA-ANN models reach their optimal performance. The mutation probability was set at 25% and the recombination rate at 9%. A single-point crossover operation with a probability of 70% was also suggested. The hybrid model incorporated the $(4 \times 5 \times 1)$ artificial neural network that had previously demonstrated the best performance. When the population size was changed but the number of iterations was maintained at 500, most hybrid GA-ANN models reached their optimal function value before 500 iterations.

The hybrid GA-ANN model results indicate that increasing the population size often leads to a higher coefficient of determination (R^2) and a lower mean square error (MSE). However, this trend was not consistent across all models. Therefore, we applied a ranking system based on both the coefficient of determination (R^2) and the corresponding mean square error (MSE), as proposed by Zorlu et al. [63], to identify the optimal population

size for the hybrid GA-ANN model in this study. Table 9 shows that a population size of 400 (pop = 400) was considered optimal. At this population size, the model achieved the best overall rank (Total rank = 50), with a coefficient of determination (R^2) of 0.9493 and a mean square error (MSE) of 0.0187 for the training datasets and an R^2 of 0.9508 and an MSE of 0.1578 for the testing datasets.

Therefore, the hybrid GA-ANN model was configured with the following optimal parameters: population size pop = 400; number of iterations Ge = 500; TolFun = 10^{-8} ; mutation probability of 25%; recombination percentage of 9%; single-point crossover operation with 70% probability. The optimal parameters for the artificial neural network (ANN) model included a TANSIG transfer function and a hidden layer with N = 5 neurons.

Table 9. Ranking the performance of hybrid GA-ANN models with varying population sizes [61].

Model	Popula- tion Size	GA-ANN Results								
		Training			Testing				Total Rank	
		R ²	Rank	MSE	Rank	R ²	Rank	MSE		Rank
1	25	0.214	1	0.3465	1	0.019	1	0.5751	9	12
2	50	0.765	3	0.0850	3	0.070	2	1.0908	4	12
3	75	0.915	10	0.0347	7	0.873	9	0.0936	12	38
4	100	0.839	5	0.0588	5	0.828	6	0.9032	5	21
5	150	0.764	2	0.1231	2	0.954	14	0.1292	11	29
6	200	0.909	8	0.0328	9	0.788	5	4.0290	3	25
7	250	0.846	6	0.0557	6	0.868	8	0.0872	13	33
8	300	0.805	4	0.0703	4	0.645	3	19.213	2	13
9	350	0.911	9	0.0323	10	0.779	4	0.5836	8	31
10	400	0.949	14	0.0187	14	0.950	12	0.1578	10	50
11	450	0.947	13	0.0190	13	0.951	13	0.8288	6	45
12	500	0.904	7	0.0346	8	0.887	10	58.594	1	26
13	550	0.944	12	0.0210	12	0.939	11	0.0363	14	49
14	600	0.941	11	0.0212	11	0.851	7	0.7892	7	36

2.6. The Hybrid PSO-ANN Model

2.6.1. Contents of the Hybrid PSO-ANN Model

While artificial neural network (ANN) models offer many benefits for predicting and calculating the area of a tunnel face after blasting, they also have drawbacks, such as a tendency to become stuck in a local minimum. Particle swarm optimization (PSO) is a technique used to help ANN models overcome this limitation.

In 1995, Kennedy and Eberhart introduced the particle swarm optimization (PSO) algorithm [64]. PSO simulates a bird swarm, modeling the social behavior of organisms (individuals) in swarms. Each individual in the swarm is considered a particle. Within the PSO algorithm, particles make decisions based on two primary factors: their own best past performance and the past best performance of the entire swarm. Initially, the particles are randomly distributed throughout the search space, with each particle representing a potential solution. The swarm operates with an objective function, and each particle's fitness is evaluated based on its corresponding value within that function. After evaluating the swarm's fitness, the velocities of all particles are updated using Equation (8), considering both the swarm's best position and each particle's individual best position. Subsequently, the next position of each particle is determined by its velocity, using Equation (9). These steps are repeated until a termination criterion is met. The termination criteria for the PSO algorithm can be based on a maximum number of iterations, a specific level of accuracy, or a combination of both [64].

$$\vec{v}_{new} = \vec{v} + C_1 \times (\vec{p}_{best} - \vec{p}) + C_2 \times (\vec{g}_{best} - \vec{p}) \quad (8)$$

$$\vec{p}_{new} = \vec{p} + \vec{v}_{new} \quad (9)$$

where $\vec{v}_{new}$ is the new velocity, $\vec{p}_{new}$ is the new particle position, $\vec{v}$ is the current velocity, $\vec{p}$ is the current position of particles in the swarm, C_1 and C_2 are the coefficients of determination in the velocity equation of the particles in the swarm, $\vec{p}_{best}$ is the best position of an individual particle in the swarm, and $\vec{g}_{best}$ denotes the global best position of all particles.

Equation (10) describes the relationship between the new velocities of particles in the swarm and their inertial weights. The inertial weight controls how much a particle's previous velocity influences its current velocity. Increasing this inertial weight can speed up the convergence of the PSO algorithm [63]:

$$\vec{v}_{new} = w \times \vec{v} + C_1 \times (\vec{p}_{best} - \vec{p}) + C_2 \times (\vec{g}_{best} - \vec{p}) \quad (10)$$

where w is the inertial weight.

In this study, as well as in the hybrid GA-ANN model, the hybrid PSO-ANN model used real data from the construction of the Deo Ca tunnel, in the form of 136 datasets. Of these, 80% were used for training, and 20% were used for testing.

2.6.2. Parameters of the Hybrid PSO-ANN Model

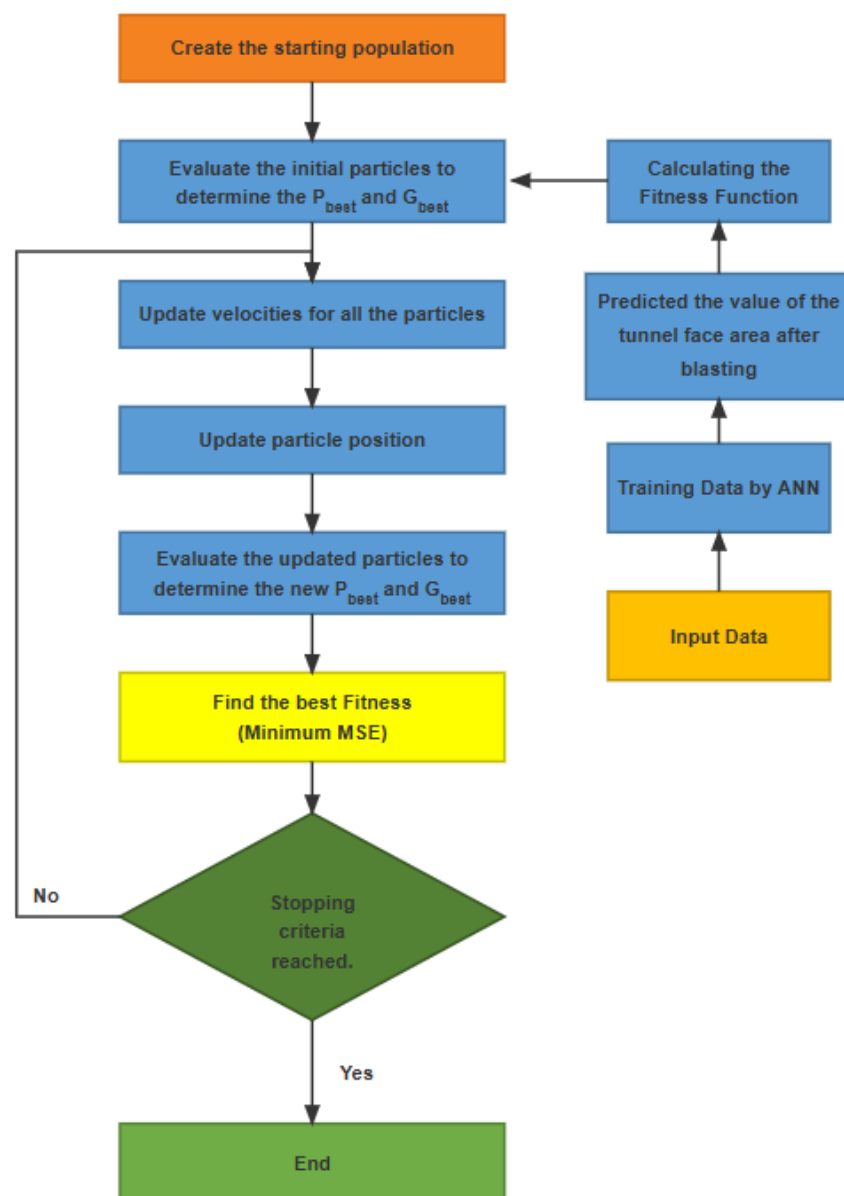
The backpropagation (BP) algorithm is widely used in artificial neural network (ANN) models. However, because it is a local search learning algorithm, the BP algorithm may not find the optimal solution for the ANN model, potentially leading to incorrect results. In contrast, the particle swarm optimization (PSO) algorithm is a powerful search method that can adjust the weights and biases within ANN models, improving their performance (Figure 13). The PSO algorithm helps the ANN model overcome local minima, increasing the likelihood of finding the global optimum. Therefore, our hybrid PSO-ANN model combines the search strengths of the ANN model and the PSO algorithm.

1. The swarm size of the PSO-ANN model

This study employed a series of swarm size sensitivity analyses to determine the optimal number of seeds for the hybrid PSO-ANN model. For each swarm size tested, the analyses were run with 1000 iterations. The velocity of particles within the swarm was determined using an equation with two coefficients, $C_1 = 2.286$ and $C_2 = 1.714$, with an inertial weight of 0.25. The hybrid PSO-ANN model utilized a 4x5x1 ANN architecture. The purpose of the sensitivity analysis was to identify the minimum mean squared error (MSE) and maximum R-squared (R^2) value for the network. Table 10 presents the results of the sensitivity analysis for the selected training and testing datasets, using swarm sizes ranging from 25 to 500. The R^2 and MSE values in this table were calculated based on the training and testing datasets used for each model.

Table 10. Results of hybrid PSO-ANN models using various swarm sizes.

Model	Swarm Size	PSO-ANN Results								
		Training				Testing				Total Rank
		R ²	Rank	MSE	Rank	R ²	Rank	MSE	Rank	
1	25	0.920	1	0.0293	2	0.879	3	0.13065	2	8
2	50	0.946	2	0.0194	3	0.948	6	0.05114	8	19
3	75	0.950	4	0.0180	5	0.952	9	0.03593	9	27
4	100	0.946	3	0.0193	4	0.948	7	0.06733	7	21
5	150	0.952	7	0.0172	7	0.689	1	0.34053	1	16
6	200	0.952	8	0.0172	7	0.958	11	0.02491	11	37
7	250	0.952	9	0.0171	8	0.837	2	0.12382	3	22
8	300	0.950	5	0.0179	6	0.917	5	0.07579	6	22
9	350	0.953	11	0.0168	9	0.952	8	0.11582	4	32
10	400	0.953	10	0.0666	1	0.883	4	0.09505	5	20
11	450	0.950	6	0.0179	6	0.957	10	0.02779	10	32

**Figure 13.** Flow chart of the hybrid PSO-ANN model's logic [19].

Generally, larger swarm sizes tend to result in higher coefficients of determination (R^2) and lower mean squared error (MSE) values. However, this trend is not consistent across all studies. Because it can be difficult to determine the best model at this stage, we used the straightforward ranking method developed by Zorlu et al. [63] to identify the optimal swarm size. This method ranks each performance metric for each class, assigning the highest rating to the best metric. Then, the ratings for the training and testing datasets are combined for each model, as shown in the “Total rank” column of Table 10. According to these total ranking values, model 6 demonstrated superior performance. Therefore, a swarm size (S_{ws}) of 200 was chosen for the hybrid PSO-ANN model to predict and determine the tunnel face area after blasting.

2. Termination criteria for the optimal algorithm in the hybrid PSO-ANN model

Termination criteria are conditions that must be met for an iterative process to stop. Generally, these criteria involve one of two conditions: either the desired exact value is reached, or the maximum number of iterations is exceeded.

In this study, the maximum number of iterations served as the termination criterion. As previously mentioned, the training time generally increases with the maximum number of iterations. However, prior research indicates that there is no universally accepted method for determining this maximum number. Therefore, we conducted a series of sensitivity analyses on the PSO-ANN model to determine an appropriate value. These analyses were performed with the following fixed parameters: 1000 iterations, particle velocity coefficients of $C_1 = 2.286$ and $C_2 = 1.714$ (Armaghani D.J et al. [19]), and an inertia weight of $w = 0.25$. The purpose of the sensitivity analysis was to track changes in the cost function (MSE) after each iteration. The results of this sensitivity analysis, conducted for swarm sizes ranging from 25 to 500, showed significant changes in the MSE during the initial iterations, followed by moderate changes up to iteration 500. After this point, no significant changes in the MSE were observed. Based on these findings, we initially selected 500 as the maximum number of iterations for the PSO-ANN model in predicting the tunnel face area after blasting. However, to further increase the model’s accuracy, we ultimately used 1000 iterations. We found that most models achieved their optimal function value before reaching the iteration limit, indicating that the optimal function value remained constant despite continued iteration.

3. Determining the coefficients C_1 and C_2 of the velocity equation in the hybrid PSO-base ANN model

In the particle swarm optimization (PSO) algorithm, C_1 and C_2 are coefficients used in the velocity update equation. A larger C_1 value promotes faster convergence of the velocity equation. Conversely, increasing the value of C_2 allows the algorithm to explore a wider range of solutions within the micro search space. Many studies initialize these coefficients with $C_1 = C_2 = 2$, and previous research established that C_1 and C_2 should satisfy $C_1 + C_2 = 4$ (Kennedy and Eberhart. [64]).

Based on the initial coefficients C_1 and C_2 proposed by Kennedy and Eberhart. [64], along with the modified coefficients by Clerc and Kennedy. [65], a variety of C_1 and C_2 values were used in this study.

Table 11 presents various combinations of C_1 and C_2 and their corresponding results. As shown above, 18 models were developed, and their results, based on R^2 and MSE values, were used for training and testing datasets. These models were built using the parameters derived in the preceding sections. A straightforward ranking method was employed to identify the optimal combination. According to the total rating values in Table 11, model 6 ($C_1 = 2.286$, $C_2 = 1.714$) performed better than the other models. Therefore, the C_1 and C_2 values from this model were selected as the coefficients for the velocity equation in this study.

Table 11. Results of hybrid PSO-ANN models with different values of C_1 and C_2 .

Model	C ₁	C ₂	PSO-ANN Results								Total Rank
			Training			Testing					
			R ²	Rank	MSE	Rank	R ²	Rank	MSE	Rank	
1	2.0	2.0	0.946	9	0.0193	7	0.728	1	0.2151	2	19
2	2.5	1.5	0.952	17	0.0172	14	0.945	11	0.0446	10	52
3	3.0	1.0	0.948	10	0.0186	8	0.949	14	0.0431	11	33
4	0.8	3.2	0.953	18	0.0169	15	0.917	8	0.1262	5	46
5	1.333	2.667	0.951	14	0.0177	12	0.947	13	0.0313	14	53
6	2.286	1.714	0.952	16	0.0172	14	0.958	17	0.0249	16	63
7	3.6	0.4	0.941	3	0.0212	4	0.957	16	0.0238	18	41
8	3.0	2.0	0.919	2	0.0304	1	0.902	5	0.0580	8	16
9	1.0	2.0	0.941	5	0.0212	4	0.759	2	0.1631	4	15
10	1.5	2.0	0.952	15	0.0173	13	0.912	6	0.0493	9	43
11	2.5	2.0	0.943	7	0.0293	3	0.815	3	0.1149	6	19
12	2.0	2.5	0.941	4	0.0212	4	0.918	9	0.0626	7	24
13	1.714	2.286	0.949	13	0.0183	11	0.832	4	0.3999	1	29
14	2.667	1.333	0.948	11	0.0185	9	0.946	12	0.0314	13	45
15	0.4	3.6	0.948	12	0.0184	10	0.929	10	0.0383	12	44
16	2.0	3.0	0.917	1	0.03	2	0.914	7	0.1891	3	13
17	2.0	1.0	0.942	6	0.0209	5	0.949	15	0.0306	15	41
18	2.0	1.5	0.945	8	0.0198	6	0.959	18	0.0241	17	49

4. Inertia weight (w) for the PSO-ANN model

The inertial weight (w) is a critical parameter in the hybrid PSO-ANN model because it significantly influences both the model's accuracy and its processing time. Clerc and Kennedy. [65] proposed several inertial weights (0.25, 0.5, 0.75, and 1), while Momeni et al., 2015 [66], suggested an inertial weight of 0.25 for predicting the Uniaxial Compressive Strength (UCS) of granite and limestone samples. Based on these values (0.25, 0.5, 0.75, and 1), we constructed four hybrid PSO-ANN models, as detailed in Table 12. These models were built using the PSO parameters obtained previously and employed the optimal architecture ($4 \times 5 \times 1$, with 4 neurons in the input layer, 5 neurons in the hidden layer, and 1 neuron in the output layer) derived from the artificial neural network (ANN) model proposed earlier. The results were analyzed and recorded based on the R^2 and MSE values, with a rank assigned to each R^2 and MSE value for the training and test datasets. Considering the sum of rank values presented in Table 12, it can be concluded that an inertial weight of 0.25 yields the best performance for the hybrid PSO-ANN model in predicting and calculating the tunnel face area after blasting.

Table 12. Results from the hybrid PSO-ANN model using different weight (w) values.

Model	Inertia Weight (w)	PSO-ANN Network Results								
		Training			Testing				Total Rank	
		R ²	Rank	MSE	Rank	R ²	Rank	MSE		Rank
1	0.25	0.952	4	0.0172	4	0.958	4	0.0249	4	12
2	0.5	0.948	3	0.0187	3	0.930	1	0.0437	2	9
3	0.75	0.939	2	0.0218	2	0.940	2	0.0321	3	9
4	1.0	0.895	1	0.0456	1	0.942	3	0.0447	1	6

3. Results and Discussion

The results in Section 2.4 indicate that the machine learning model, which uses artificial neural networks (ANN), accurately predicts and calculates the tunnel face area after blasting. Therefore, the ANN model should be optimized by combining available optimization algorithms, specifically particle swarm optimization (PSO) and genetic algorithm (GA). K-fold cross-validation (Diamantidis et al.) was used to evaluate model performance [62,67]. This technique divides the data into K parts. (K – 1) parts are used for training the model, and one part is used for testing. With our initial database of 136 entries, we divided the data into five random parts, using four parts for training and one part for testing. To select the most accurate model, we considered the coefficient of determination (R^2) and mean squared error (MSE) for each model. However, because the differences in the R^2 and MSE values were very small, we ranked the models based on their R^2 and MSE values for each training and testing dataset. The results are shown in Tables 13 and 14.

Table 13. Model ratings.

Method	Model	Training				Testing				Sum Rank
		R^2	Rank	MSE	Rank	R^2	Rank	MSE	Rank	
ANN	1	0.948	5	0.01969	5	0.901	4	0.03383	6	20
	2	0.935	2	0.02346	2	0.843	2	0.05951	2	8
	3	0.949	6	0.01876	7	0.919	6	0.02838	10	29
	4	0.951	8	0.01678	9	0.909	5	0.04633	3	25
	5	0.948	4	0.02001	4	0.928	12	0.02241	13	33
GA-ANN	1	0.943	3	0.02130	3	0.919	7	0.03	9	22
	2	0.954	11	0.01600	11	0.879	3	0.0459	4	29
	3	0.956	14	0.01580	12	0.926	11	0.0255	12	49
	4	0.956	15	0.01560	13	0.940	14	0.0302	8	50
	5	0.914	1	0.03240	1	0.691	1	0.0991	1	4
PSO-ANN	1	0.953	10	0.01720	8	0.923	9	0.0275	11	37
	2	0.956	13	0.01540	14	0.920	8	0.0304	7	42
	3	0.953	9	0.01680	10	0.938	13	0.0224	13	46
	4	0.955	12	0.01530	15	0.924	10	0.0344	5	42
	5	0.949	7	0.01890	6	0.941	15	0.0187	15	43

Table 14. Average values of coefficients of determination (R^2) and mean square error (MSE) of different models.

Method	Training		Testing	
	R^2 Average	MSE Average	R^2 Average	MSE Average
ANN	0.946	0.0197	0.900	0.0381
GA-ANN	0.944	0.0202	0.871	0.0461
PSO-ANN	0.953	0.0167	0.929	0.0267

From the results obtained using models with different algorithms, as shown in Figures 14–20 and Tables 13 and 14, we observed the following:

- The optimal model using the hybrid GA-ANN model (a genetic algorithm combined with an artificial neural network) demonstrated the best performance and accuracy, with $R^2_{\text{training}} = 0.9562$, $R^2_{\text{testing}} = 0.94$, $\text{MSE}_{\text{training}} = 0.0156$, and $\text{MSE}_{\text{testing}} = 0.0302$. The optimal hybrid PSO-ANN (the particle swarm optimization PSO algorithm combined with the artificial neural network ANN) model achieved the next best results, with $R^2_{\text{training}} = 0.9536$, $R^2_{\text{testing}} = 0.9387$, $\text{MSE}_{\text{training}} = 0.0168$, and $\text{MSE}_{\text{testing}} = 0.0224$. The

optimal ANN model performed the worst (lowest model accuracy), with $R^2_{\text{training}} = 0.948$, $R^2_{\text{testing}} = 0.9288$, $\text{MSE}_{\text{training}} = 0.02$, and $\text{MSE}_{\text{testing}} = 0.0224$;

- Due to the use of random data, the results of these algorithms can vary, depending on the size and quality of the database used for training and testing. For the hybrid GA-ANN model (the genetic algorithm combined with an artificial neural network), the population size was a key parameter that required optimization for each model. Similarly, for the hybrid PSO-ANN model (particle swarm optimization combined with an artificial neural network), the parameters to be optimized included the swarm size, the velocity coefficients C_1 and C_2 , and the initial weight w .
- The use of hybrid models (GA-ANN and PSO-ANN) improved the accuracy of the model results. However, the processing time required by these hybrid models also tended to increase proportionally to their accuracy. In the GA-ANN hybrid model, in which the genetic algorithm (GA) is used to optimize the ANN model, the average processing time to produce results with the same input dataset used in this study was 3862.65 s. For the hybrid PSO-ANN model, the average processing time with the same input dataset was 1867.8 s. In comparison, the ANN model alone processed the same data in just 8 to 25 s. The computer used has the following specifications: Core i7, 7820 HQ configuration, 3.2 GHz CPU, and 16 GB of RAM.
- Genetic algorithms (GAs) and particle swarm optimization (PSO) differ in their mechanisms. A GA uses genetic operations, such as crossover and mutation, to evolve solutions. PSO, on the other hand, uses social interaction and individual memory to guide particle movement. Regarding information sharing, a GA shares information indirectly through selection and crossover, while a PSO algorithm shares information directly using pbest (personal best) and gbest (global best) values. To maintain diversity, a GA relies on mutation to introduce new variations, while a PSO algorithm maintains diversity through the independent movement of particles and their stored best individual positions. In terms of suitability, GAs are often effective for a wide range of optimization problems, including discrete and combinatorial ones. PSO works especially well for continuous optimization problems and often converges more quickly. In this study, GA-ANN hybrid models outperformed PSO-ANN hybrid models in predicting the tunnel face area after blasting. This difference in performance can be attributed to the operating characteristics of the GA and PSO algorithms. Given the characteristics of the data used to build these models, some input variables exhibited significantly different properties compared to others. Consequently, the PSO algorithm, which models the social behavior of bird flocks to find optimal solutions without using genetic operators, may have been less effective. PSO relies on memorizing the best solutions found by individual particles and the entire swarm. Therefore, its predictions of the tunnel face area after blasting were not as accurate as those of the GA model, which uses selection, crossover, and mutation to evolve a set of potential solutions.

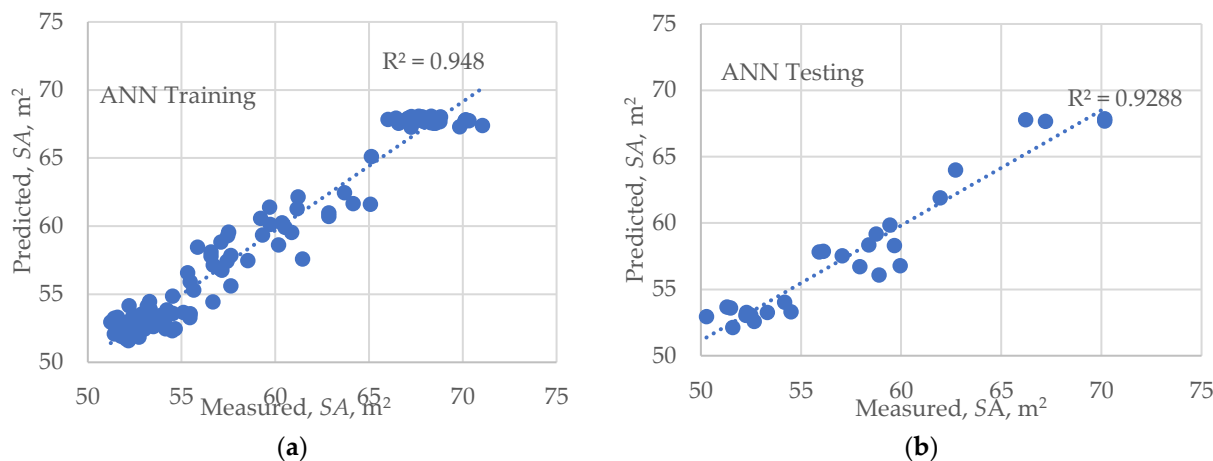


Figure 14. Measured and predicted SA obtained through optimal ANN model (a) training and (b) testing datasets.

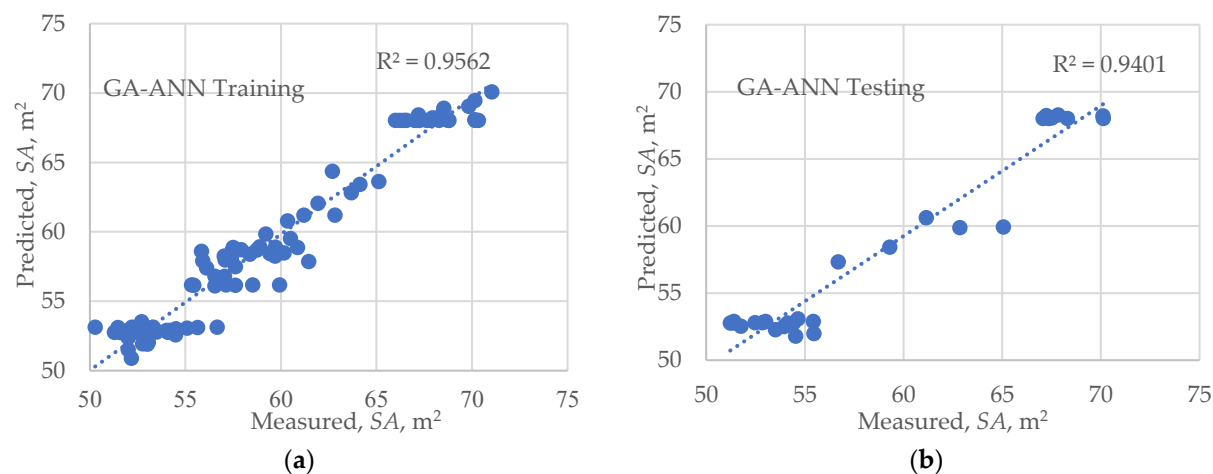


Figure 15. Measured and predicted SA obtained via the GA-ANN optimal model (a) for training and (b) testing datasets.

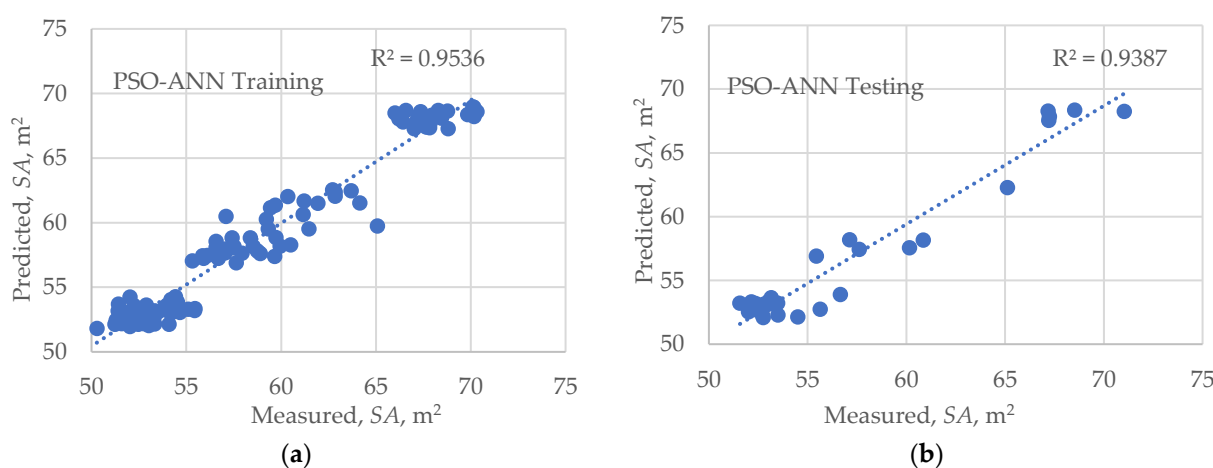


Figure 16. Measured and predicted SA obtained via the optimal PSO-ANN model (a) for training and (b) testing datasets.

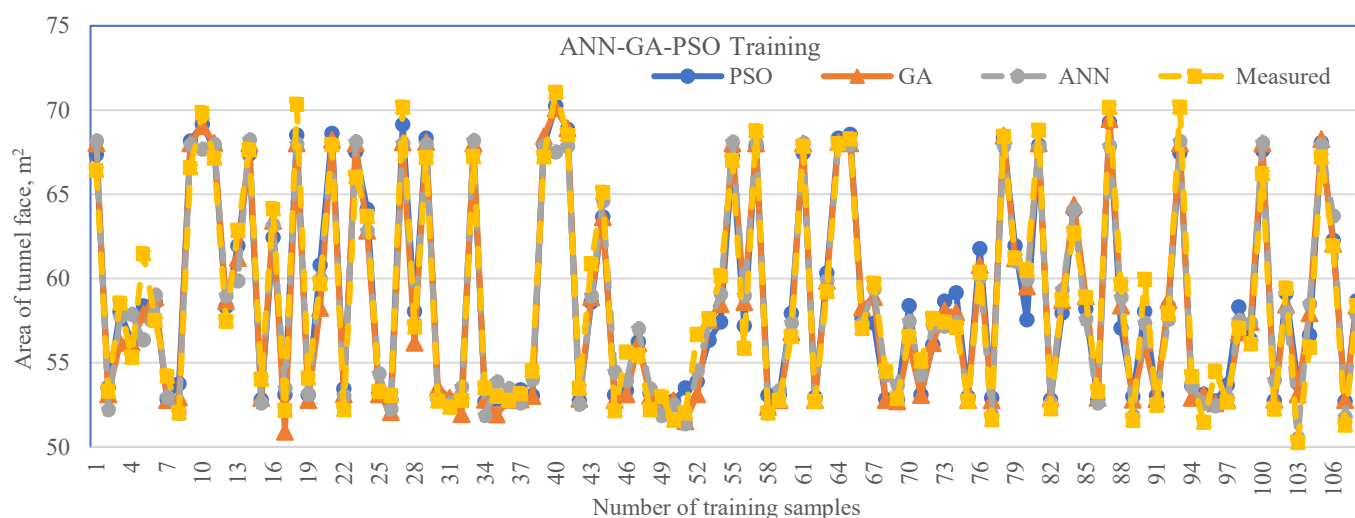


Figure 17. Comparison of measured and predicted SA for optimal PSO-ANN, ANN, and GA-ANN models using different training datasets.

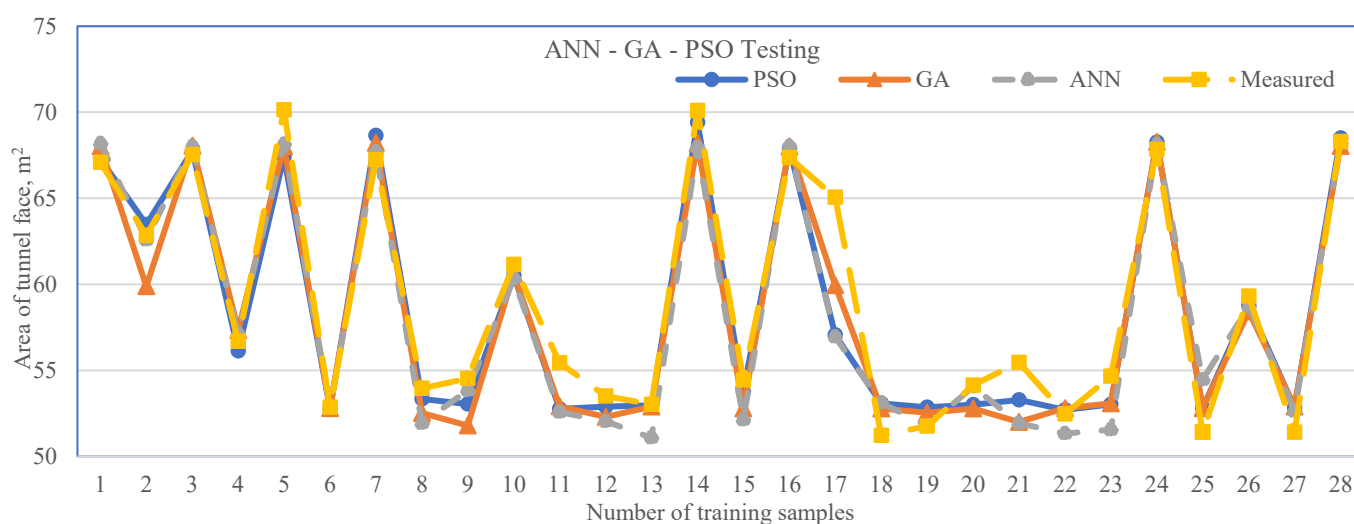


Figure 18. Comparison between measured and predicted the SA for different testing datasets in PSO-ANN, ANN, and GA-ANN optimal models.

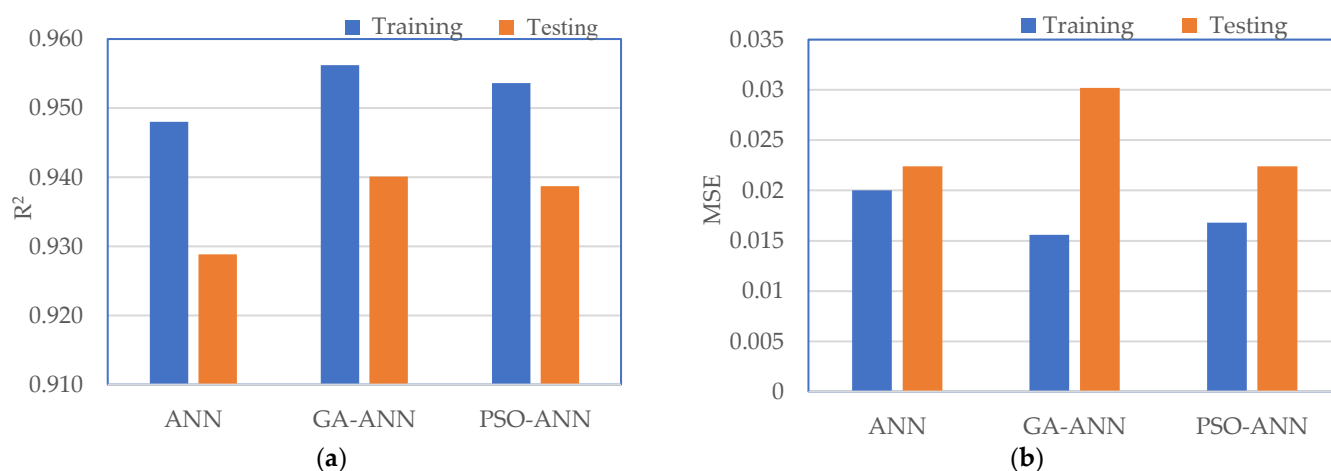


Figure 19. Comparison of ANN, GA-ANN and PSO-ANN optimal models: (a) coefficient of determination (R^2) and (b) mean square error (MSE).

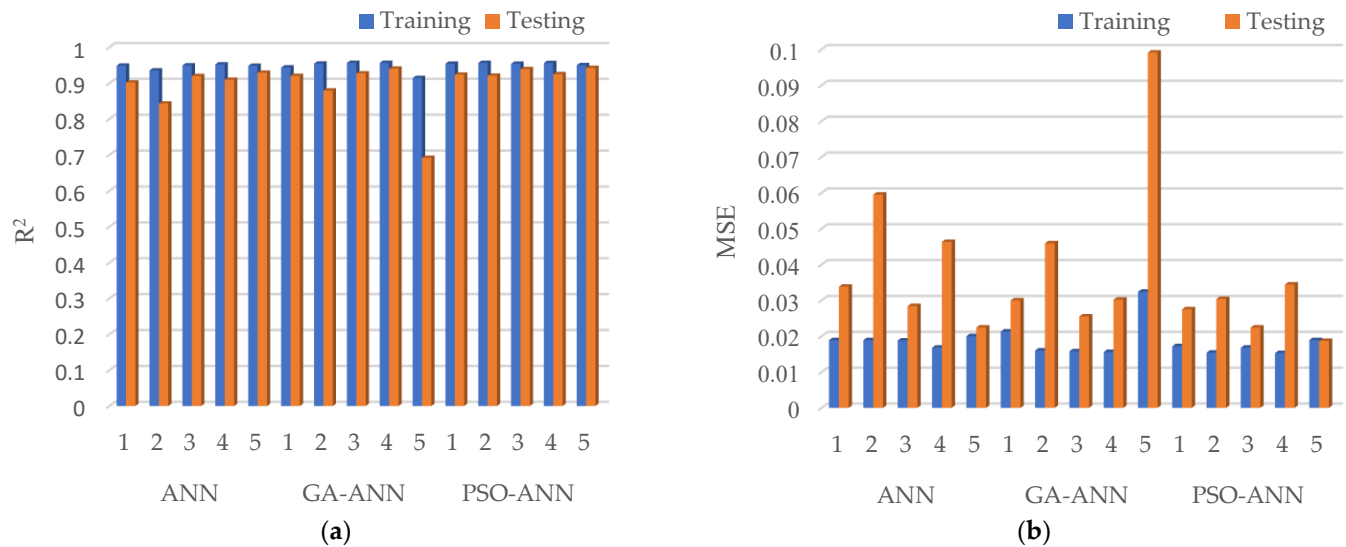


Figure 20. Comparison of ANN, GA-ANN, and PSO-ANN models: (a) coefficient of determination (R^2) and (b) mean square error (MSE) of ANN, GA-ANN, and PSO-ANN models.

4. Sensitivity Analysis

The relative influence of each parameter within the network system (sensitivity analysis) was determined using the cosine amplitude method (CAM), as described by Yang and Zhang. [68]. In this method, paired data are used to create a data array, X :

$$X = \{x_1, x_2, \dots, x_i, \dots, x_n\} \quad (11)$$

The variables x_i in array X are a vector of length m ; x_i is determined by Equation (12) [68]:

$$x_i = \{x_{i1}, x_{i2}, \dots, x_{im}\} \quad (12)$$

The equation representing the strength of the relationship between the dataset X_i and X_j is as follows [68]:

$$R_{ij} = \frac{\sum_{k=1}^m x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^m x_{ik}^2 \sum_{k=1}^m x_{jk}^2}} \quad (13)$$

Using the equations mentioned above, the relationship of the input variables (S_d , L , SC , and RMR) and the dependent output variable (SA) was calculated (Table 15).

Table 15. Strength of relationship between input and output variables.

Input Variables	The Designed Tunnel Face area, S_d	The Average Borehole Length, L	The Specific Charge, SC	The Rock Mass Rating, RMR
R_{ij}	0.99962	0.95137	0.95238	0.94946

Based on the results in Table 15 and Figure 21, among the four independent variables used to predict the tunnel face area after blasting, the designed tunnel face area (S_d) has the greatest influence on the output dependent variable: the tunnel face area after blasting (SA). The specific charge (SC) is the next most influential variable, followed by the average borehole length (L) and, finally, the rock mass rating (RMR). Therefore, we can conclude that in the model for calculating and predicting the tunnel face area after blasting, the

controllable independent variables (specific charge (SC), designed tunnel face area (S_d), and average borehole length (L)) have a greater influence on the tunnel face area after blasting (SA) than the uncontrollable variable (rock mass rating (RMR)).

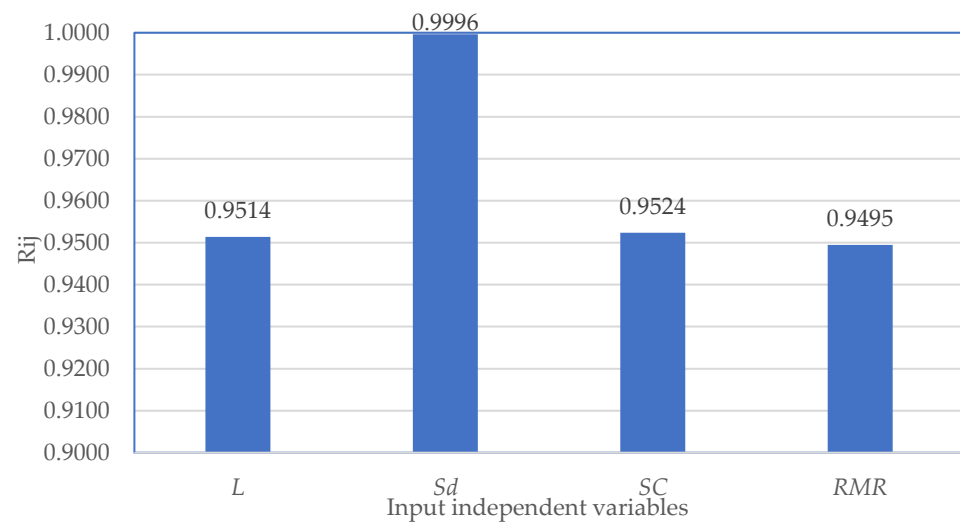


Figure 21. Strength of relationship between independent input variables and dependent output variables.

5. Suggestions and Further Study

The models studied and developed in this research suggest that the methods described can predict and calculate the post-blast tunnel cross-sectional area. Accurately predicting and calculating the value of the tunnel face area after blasting will improve efficiency while designing drilling and blasting parameters for underground projects using the D&B method. Designers can adjust the drilling and blasting parameters (the designed tunnel face area (S_d), average borehole length (L), and specific charge (SC)) to achieve the desired tunnel face area. The GA-ANN and PSO-ANN hybrid models are preferable for predicting tunnel face area after blasting because they offer high accuracy and reliability. The hybrid GA-ANN and PSO-ANN models can optimize controllable parameters to enhance the efficiency of drilling and blasting in underground construction. The GA-ANN model uses a genetic algorithm (GA) to optimize an artificial neural network (ANN). Similarly, the PSO-ANN model combines a particle swarm optimization (PSO) algorithm with an ANN. These hybrid models improve the prediction and calculation of the tunnel face area after blasting. For artificial intelligence models like the GA-ANN and PSO-ANN to function effectively, large and accurate input and output datasets are essential. These datasets require processing and standardization before they can be used to create AI models. The next phase of this research will focus on automating systems for collecting and combining data for AI models to create a large, real-time datasets. Researchers will also explore and implement new optimization algorithms to develop hybrid models that can accurately predict the tunnel face area after blasting. This will enable continuous updates and adjustments to the design and construction of tunnels using the drilling–blasting method. By adapting to the specific geotechnical conditions of the construction area, this approach helps ensure the progress and stability of tunnel construction.

6. Conclusions

The post-blast tunnel cross-sectional area is a key factor in evaluating the effectiveness of blasting for tunnel construction. Currently, estimations of this area rely on geological conditions at the tunnel site, as well as tunnel parameters such as the designed tunnel face area, tunnel cross-section shape, borehole characteristics, and the types of explosives

used. This study used SPSS IBM 2022 and MATLAB 2019 b software to develop models for determining the post-blast tunnel cross-sectional area. These models included multiple linear regression analysis (MLRA), multiple nonlinear regression (MNLN), artificial neural networks (ANNs), a hybrid genetic algorithm–artificial neural network (GA-ANN) model, and a hybrid particle swarm optimization–artificial neural network (PSO-ANN) model. A total of 136 datasets, collected during the construction of the Deo Ca tunnel in Phu Yen, Vietnam, were used to investigate the parameters affecting the tunnel face area after blasting. These datasets were used to successfully build the models mentioned above. Of the 136 datasets, 80% were randomly selected for use as training data, and 20% were used as testing data for all models. By using the developed models and comparing their calculated results with measurements obtained during actual tunnel construction, the following conclusions can be drawn:

- Both multiple linear regression analysis (MLRA) and multiple nonlinear regression (MNLN) models can accurately calculate and predict the area of a tunnel face after blasting. However, the multiple nonlinear regression (MNLN) model provides more accurate results than the multiple linear regression analysis (MLRA) model.
- This study employed deep learning, specifically an artificial neural network (ANN), to predict the area of a tunnel face after blasting with greater accuracy than multiple linear regression analysis (MLRA) and multiple nonlinear regression (MNLN) models. The ANN model's prediction performance (R^2) in both the training and testing datasets surpassed that of the multiple linear regression analysis (MLRA) model and the multiple nonlinear regression (MNLN) model.
- The results obtained with the ANN model informed the optimal architecture for the ANN model (in this study, $4 \times 5 \times 1$ was chosen as the best architecture for the ANN model).
- Hybrid models can be useful in predicting the area of a tunnel face after blasting. These models combine artificial neural networks (ANNs) with optimization algorithms, like genetic algorithms (GAs) or particle swarm optimization (PSO). However, building these models necessitates determining the optimal parameter settings for the algorithms they employ.
- Combining a genetic algorithm (GA) and particle swarm optimization (PSO) with an artificial neural network (ANN) resulted in models capable of predicting and calculating the area of the tunnel face after blasting with very high accuracy. However, these hybrid models require more powerful hardware and longer processing times compared to ANN models alone. Based on a ranking method using selected performance indices, the best hybrid GA-ANN models were identified ($R^2_{\text{training}} = 0.9562$; $R^2_{\text{testing}} = 0.94$ and $\text{MSE}_{\text{training}} = 0.0156$; $\text{MSE}_{\text{testing}} = 0.0302$). However, as indicated in Table 14, the PSO-ANN models exhibited the highest mean accuracy when evaluating the aggregate performance of the GA-ANN, PSO-ANN, and ANN architectures.
- By analyzing the influence of the parameters (input variables) of the geological environment surrounding the tunnel, the parameters of the tunnel, and the explosives used in the tunnel construction could be determined. In conclusion, the designed tunnel face area S_d is the most influential input variable regarding the models' results.
- Using a dataset with varying ranges of input variables—including the designed tunnel face area (S_d), specific charge (SC), average borehole length (L), and rock mass rating (RMR)—enables both the artificial intelligence model and the statistical model to predict the area of the tunnel face after blasting across a broad spectrum of input values. However, when the input data fall outside the ranges present in this dataset, the parameters and characteristics of both models must be adjusted to ensure that they maintain accuracy when predicting the tunnel face area after blasting.

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