

Optimizing an Artificial Intelligence Model to Predict The Tunnel Face Area after Blasting

DO Hoang Hiep¹, BUI Manh Tung¹, NGUYEN Chi Thanh^{1,2,*}

¹ Hanoi University of Mining and Geology, 18 Vien Street, Hanoi, Vietnam

² Tunnelling and Underground Space Technology, Vietnam

* Corresponding author: nguyenchithanh@humg.edu.vn

Abstract: *In underground tunnel construction for mining, the drilling and blasting method is widely used due to its advantages, such as low cost, simple calculation and implementation, and applicability in various geological and hydrogeological conditions. The drilling and blasting method is also suitable for tunnels with different cross-sectional shapes. One parameter that significantly influences the effectiveness of the drilling and blasting method is the area of the tunnel face after blasting. In this study, 136 datasets of influencing parameters and the tunnel face area after blasting from the DeoCa tunnel construction project were used to develop an artificial neural network (ANN) model capable of predicting the tunnel face area after blasting. The paper developed an ANN model and proposed a hybrid model based on the ANN model combined with a genetic algorithm (GA) to predict the area of the tunnel face after blasting. The input variables for the models included the designed tunnel face area (S_d), the specific charge (SC), the average borehole length (L), and the rock mass rating (RMR) of the rock mass on the tunnel face. This paper demonstrates that the hybrid GA-ANN model provides more accurate calculations and predictions for the tunnel face area after blasting than the ANN model alone.*

Keywords: Tunnel face area; artificial neural network (ANN); genetic algorithms (GA); blasting; prediction

1. Introduction

The drilling and blasting method is a primary technique used in underground construction, particularly in mines. Its advantages include low cost, simple technique, and high effectiveness in various geological conditions and with different tunnel cross-sectional shapes. However, applying this method also presents challenges. One major problem is the occurrence of overbreak and underbreak, where the blasted tunnel face deviates from the designed area. This reduces the efficiency of blasting in underground construction, impacting the volume of subsequent work, such as tunnel support structures and the amount of rock to be removed. The area of the tunnel face after blasting is a key factor in evaluating the method's effectiveness, including the extent of overbreak and underbreak. Accurately determining this area, however, is difficult. Existing methods are often unsuitable for diverse conditions or provide inaccurate results compared to experimental findings. This difficulty stems from the complexity of predicting the tunnel face area after blasting, which is influenced by numerous parameters.

The area of a tunnel face after blasting can depend on several parameters, including geological conditions, the type of explosives used, and the shape of the tunnel's cross-section, or a combination of these factors. These parameters can be divided into two main groups: controllable and non-controllable. Controllable parameters include blasting techniques and the shape of the tunnel's cross-section. Non-controllable parameters encompass the geological and hydrogeological conditions of the tunnel's location. Some researchers also consider the shape of the tunnel's cross-section as a third group, referred to as semi-controllable parameters. According to several studies (Lawal AI, Kwon S., 2021; Jang and Topal, 2013; Dey, K., Murthy, V.M.S.R., 2012; Chakraborty et al., 2004; Murthy, V.M.S.R et al., 2003; Innaurato et al., 1998; Ibarra, J.A et al., 1996), non-controllable parameters, such as geological conditions, hydrogeology, and the unconfined compressive strength (UCS) of the rock, significantly influence the area of the tunnel face after blasting. The fracturing of rock through blasting results from blast waves propagating through the rock mass. Harder rock allows these blast waves to travel faster and more effectively, leading to greater rock destruction. However, the velocity of blast waves is also highly dependent on the joint systems present within the rock mass. The width and size of these joint systems, along with the properties of any filling material within them, affect the impact of the blast wave, consequently influencing the area of the tunnel face after blasting (Mandal et al., 2008; Singh et al., 2011, Shiwei et al., 2013; Mottahedi et al., 2018, Chi

T. N et al., 2022).

This study uses hybrid models built with artificial neural networks (ANNs) combined with optimization algorithms, specifically genetic algorithms (GAs), to identify the tunnel face area after blasting. The results demonstrate the advantage of artificial intelligence in determining and predicting the tunnel face area after blasting. This approach considers the influence of both non-controllable parameters, such as the rock mass rating (RMR), and controllable parameters, such as the design tunnel face area (S_d), the specific charge (SC), and the average borehole length (L). The models that combine ANNs optimized by GAs performed particularly well.

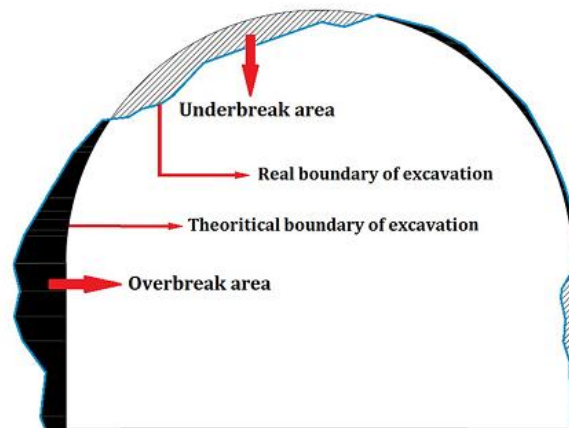


Fig. 1. The area of tunnel face after blasting (Mottahedi, A et al., 2018).

2. Case study and data

The Deo Ca traffic tunnel is situated between Phu Yen and Khanh Hoa provinces. Its total length is approximately 13.5 km, including a 4.1 km tunnel through Deo Ca mountain and a 500 m tunnel through CoMa mountain. The remaining 9 km consist of roads and bridges along the route. A total of 136 datasets were collected and used to build and verify the accuracy of models for predicting and calculating the tunnel face area after blasting. In this study, 109 datasets were used for training the models (80%), and 27 datasets were used for testing them (20%). These datasets include four input parameters: the rock mass rating (RMR), the design tunnel face area (S_d), the average borehole length (L), and the specific charge (SC). The output data is the actual tunnel face area after blasting (S_a). Among the four input parameters, the design tunnel face area (S_d), the average borehole length (L), and the specific charge (SC) are considered controllable parameters, while the rock mass rating (RMR) is classified as a non-controllable parameter. The limit and average values for all parameters are shown in Table 1.



Fig. 2. Deo Ca traffic tunnel

Tab. 1. The limit and average values of parameters in models

Parameter	Symbol	Unit	Category	Min	Max	Mean	Std. Deviation
The average boreholes length	L	m	Input	1.0	3.2	1.9569	0.6691
The design 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
The rock mass rating	RMR	-	Input	5.0	74.0	49.7982	17.1133
The actual area of the tunnel face after blasting	SA	m ²	Output	50.276	71.049	59.0051	6.3834

3. AI models

3.1. ANN model

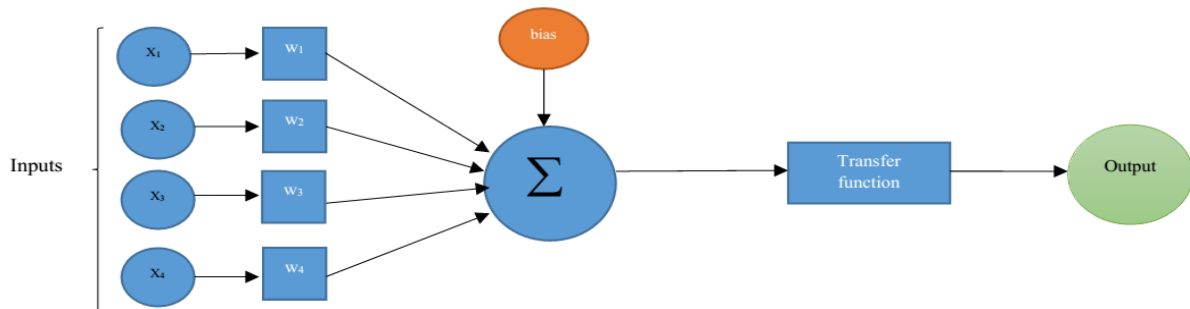


Fig. 3. Diagram of the artificial neural network ANN in study

Artificial neural network (ANN) is a simplified mathematical reasoning model based on the working principle of the human brain, so this model is called an artificial neural network. The ANN can define complex relationships between input variables to simulate one (or more) output variable(s) (Specht, 1991). A particular ANN model can be defined through important components such as transfer function, neural network structure, and neural network learning rules (Simpson, 1990). Regarding the operation and accuracy of the artificial neural network (ANN), it is necessary to define the initial set of weights and show how these weights are modified during the training of the neural network to increase neural network accuracy (Monjezi and Dehghani, 2008). In this study, it is proposed to use only one hidden layer of neurons and use the BP back-propagation algorithm in the neuron model. Basically, the training of a neural network according to the backpropagation (BP) algorithm involves two steps in different layers of the network, namely forward and backward. In relaying, the input signal is applied to nodes of the network and its effect propagates through each network layer. Finally, an output is generated as the actual response of the network. If the response differs from the desired value, error correction is required to adjust the weights and bias in the network to match the error value.

In the backpropagation (BP) algorithm, input data is fed into the input layer and propagates through the network until an output is produced. Each neuron then calculates its weighted input using the following equation (Simpson, 1990):

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

Where, X is 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, respectively, n is the number of input data, β is the threshold applied to the neuron that is processing the data.

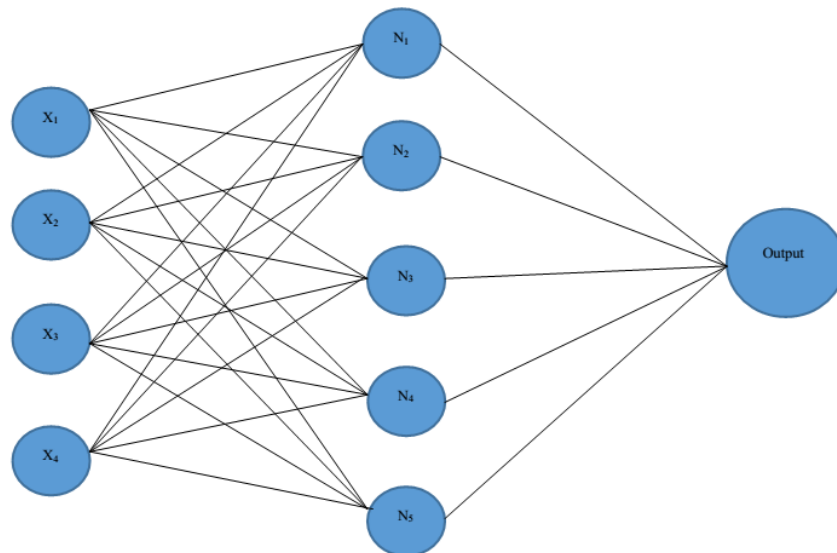


Fig 4. Structure of the artificial neural network (ANN) used in this study (Chi T. N et al., 2022).

In this study, to construct an artificial neural network (ANN) for predicting the area of a tunnel face after blasting, the data used for training and testing the ANN model must first be processed. Because the transfer function used in the ANN model is the TANSIG function, the data must be normalized to the interval $[-1, 1]$ according to the following equation (Monjezi and Dehghani, 2008):

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

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, $X_{\min}$ is the initial minimum value of the unnormalized variable.

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 is crucial for achieving the most accurate results (Simpson PK, 1990). Many studies have successfully employed the Levenberg-Marquardt back-propagation training algorithm in ANNs. Research suggests that an ANN with a single hidden layer can approximate any continuous function (Basheer I et al., 2001). Furthermore, using an ANN with one hidden layer simplifies the model, reduces processing time, and minimizes overfitting. For these reasons, this study utilizes an ANN with a single hidden layer. Several researchers have developed formulas to help determine the appropriate number of neurons for the hidden layer. For instance, according to Hecht-Nielsen, the number of neurons in the hidden layer should be less than or equal to $(2*N-1)$ with N is the number of neurons in the input layer (number of input neuron),

To find the appropriate number of neurons for the hidden layer of an artificial neural network (ANN) model, create several models, each with a different number of neurons in the hidden layer. Evaluate each model using training and testing datasets, and note the coefficient of determination (R^2) and the mean squared error (MSE). A reasonable number of neurons for the hidden layer will be determined based on these results. The principle for evaluating the models using R^2 and MSE is that models with a high R^2 value and a low MSE value are considered more suitable.

Where the mean square error MSE is determined through the equation (Simpson, 1990) :

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - y'_i)^2 \quad (3)$$

The coefficient of determination R^2 is determined through the equation (Simpson, 1990):

$$R^2 = \left[\frac{\sum_{i=1}^N (y - \bar{y})(y' - \bar{y}')}{\sum_{i=1}^N (y - \bar{y})^2 \sum_{i=1}^N (y' - \bar{y}')^2} \right]^2 \quad (4)$$

Where, N is the number of data at the input layer, y_i is the i^{th} actual measured value, y' is the i^{th} predicted value, respectively, $\bar{y}$ is the actual measured mean and $\bar{y}'$ is the value average prediction.

Based on the results in Tables 2 and 3, as well as the coefficient of determination (R^2) for both the training and testing datasets of the ANN model (shown in Figs. 5, 6, 7 and 8), this paper selected the number of hidden nodes for the artificial neural network (ANN). A 4x5x1 structure, with 4 neurons in the input layer, 5 neurons in the hidden layer, and 1 neuron in the output layer, represents a suitable ANN model. Using this model structure, the artificial neural network can calculate and predict the tunnel face area after blasting with high accuracy.

Tab. 2. The results of the coefficient of determination R^2 for several ANN models with different hidden nodes

The model number	Number of neurons in the hidden layer	The results of models											
		R^2											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	0.93993	0.95498	0.95278	0.79113	0.96032	0.90407	0.93689	0.94438	0.91538	0.92109	0.94727	0.90313
2	2	0.93956	0.95728	0.93390	0.94740	0.93755	0.96408	0.93273	0.92305	0.94681	0.90035	0.94472	0.93843
3	3	0.93950	0.94217	0.92149	0.92242	0.95729	0.95513	0.94494	0.93999	0.94814	0.96249	0.94770	0.94444
4	4	0.93339	0.93939	0.95055	0.94673	0.94076	0.94383	0.94147	0.91631	0.93339	0.96518	0.94568	0.94229
5	5	0.94762	0.95777	0.95388	0.93922	0.95572	0.95590	0.96734	0.92432	0.94346	0.94803	0.95684	0.94505
6	6	0.93695	0.95356	0.95249	0.86373	0.94918	0.96466	0.94162	0.90538	0.92942	0.96817	0.94768	0.93110
7	7	0.93281	0.90074	0.92459	0.95153	0.94166	0.96569	0.95567	0.93120	0.95319	0.87520	0.94596	0.92487
8	8	0.93329	0.91761	0.92730	0.94406	0.92631	0.92385	0.94538	0.91503	0.95076	0.90156	0.94199	0.92042
9	9	0.93233	0.90529	0.94418	0.93326	0.92528	0.89068	0.92594	0.91048	0.90318	0.92624	0.93344	0.91319

Tab. 3. The results of the mean squared error (MSE) for several ANN models with different hidden nodes

The model number	Number of neurons in the hidden layer	The results of models											
		MSE											
		Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 5		Average	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
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	0.01940	0.02290	0.01743	0.03182	0.01678	0.01678	0.01174	0.02277	0.02054	0.02042	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

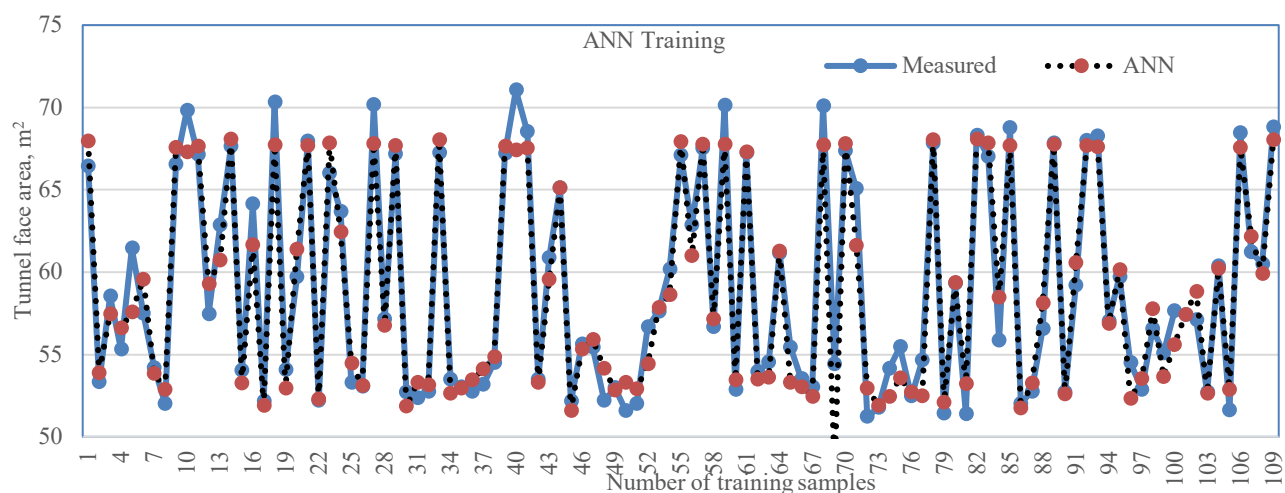


Fig. 5. Comparison between measured and predicted SA for different training datasets in ANN model

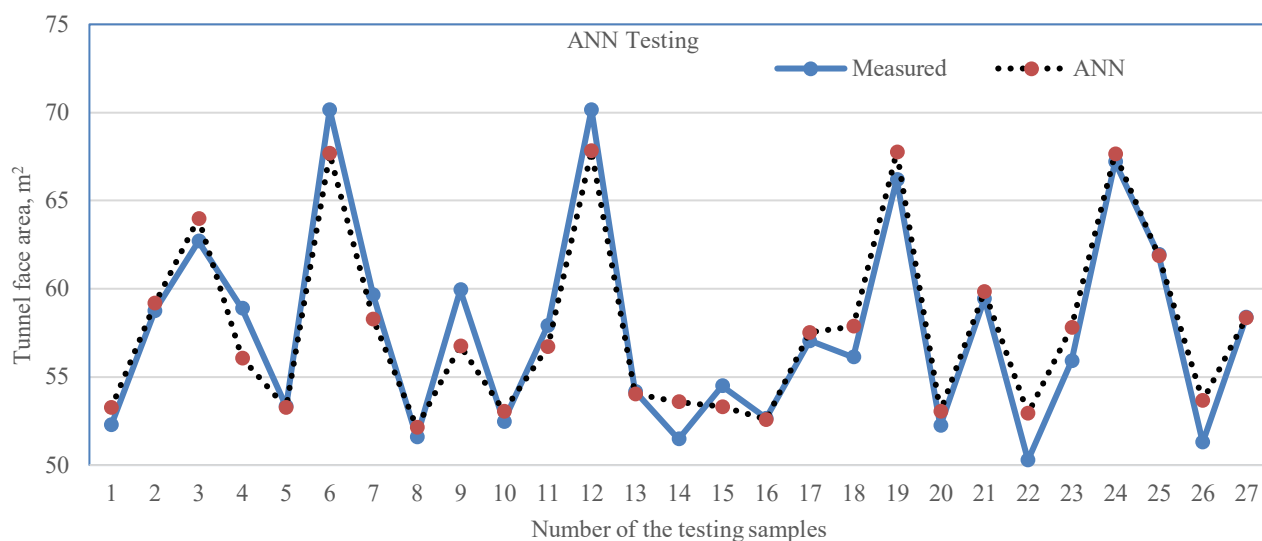


Fig. 6. Comparison between measured and predicted SA for different testing datasets in ANN model

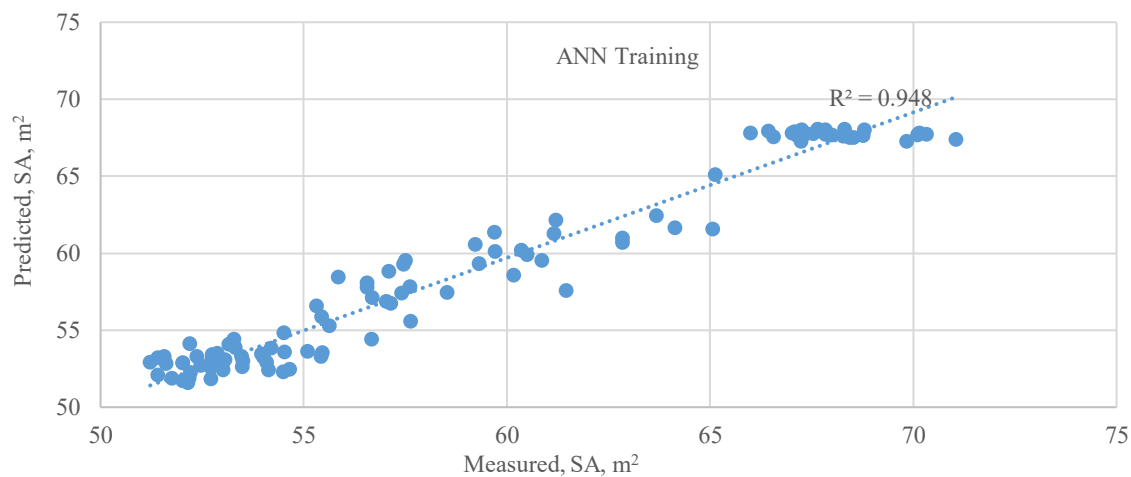


Fig. 7. Measured and predicted SA obtained via the ANN model for training database

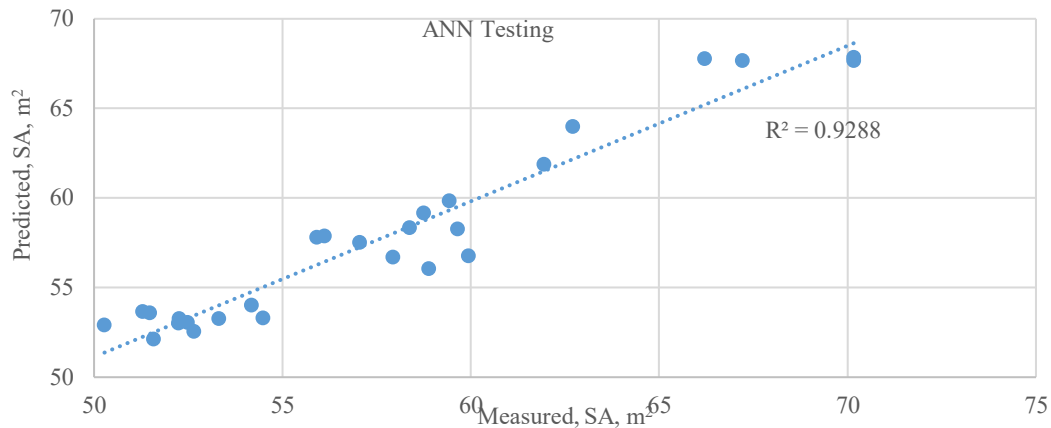


Fig. 8. Measured and predicted SA obtained via the ANN model for testing database

Figures 7 and 8 illustrate the correlation between the measured tunnel face area after blasting and the area predicted by the artificial neural network (ANN). These figures show a strong correlation between the actual and predicted values. The coefficients of determination (R^2) values for both the training and testing data indicate that the ANN model can accurately predict and calculate the tunnel face area after blasting.

3.2. The hybrid GA-ANN model

3.2.1. Genetic algorithm GA

Holland introduced the genetic algorithm (GA) in his 1975 publication. A key advantage of the GA is its ability to address complex, nonlinear problems. This study analyzes a hybrid model that combines the GA with an artificial neural network (ANN). This hybrid GA-ANN model is designed to handle complex nonlinear problems in underground construction, specifically the calculation and prediction of the tunnel face area after blasting. The hybrid model overcomes the limitations of using an ANN alone for this purpose, improving accuracy and model convergence. When using a GA, careful selection of design parameters is crucial, as these parameters significantly impact the algorithm's convergence and the overall model results.

In the hybrid GA-ANN model, the connection weight “w” is optimized as the artificial neural network (ANN) processes information at neurons within its layers. The connection weights are updated iteratively, from generation to generation, until the ANN converges on an acceptable error level or reaches the training tolerance at the output layer. In this study, the initial dataset of 136 samples is divided into two parts: a training set of 109 samples (80% of the initial data) and a testing set of 27 samples (20% of the initial data). These initial datasets were used to determine the necessary parameters for the hybrid GA-ANN model. The data for both the training and testing sets were randomly selected from the overall dataset to survey and construct the hybrid GA-ANN model.

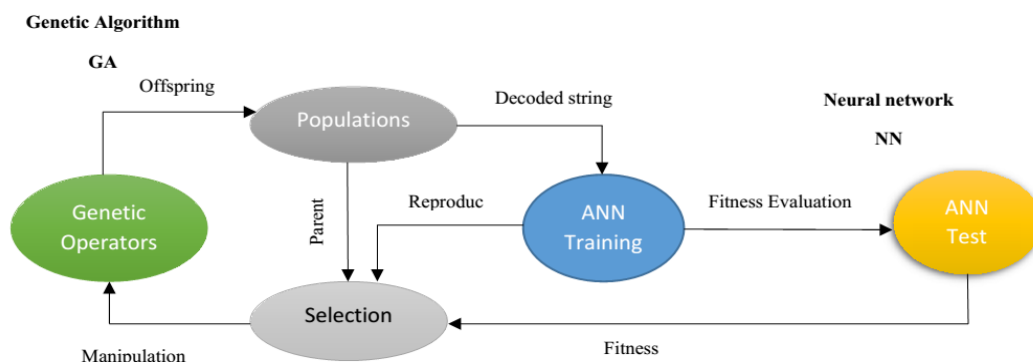


Fig. 9. The logical flow chart of hybrid GA-ANN model

3.2.2. The parameters of the GA-ANN hybrid model

To establish suitable parameters for the hybrid GA-ANN model, several models were constructed with population sizes ranging from 25 to 600. The number of iterations in the hybrid GA-ANN model was set to $Ge=500$; this value, according to previous studies by Mohamad et al. (2016), Longqi Liu et al. (2019),

and Kusum Pandey et al. (2020), represents the optimal number of iterations. The hybrid model utilizes an artificial neural network with a 4x5x1 structure, as detailed earlier in this paper. By varying the population size while keeping the number of iterations constant at Ge=500, the paper observed that nearly all models reached their optimal function value before the maximum iteration limit of Ge=500.

Tab. 4. Ranking results of hybrid GA-ANN models with different population sizes.

Model	Pops	Network results								Total rank
		Training				Testing				
		R ²	Rank	MSE	Rank	R ²	Rank	MSE	Rank	
1	25	0.2149	1	0.3465	1	0.0191	1	0.5751	9	12
2	50	0.7650	3	0.0850	3	0.0704	2	1.0908	4	12
3	75	0.9150	10	0.0347	7	0.8731	9	0.0936	12	38
4	100	0.8392	5	0.0588	5	0.8285	6	0.9032	5	21
5	150	0.7642	2	0.1231	2	0.9542	14	0.1292	11	29
6	200	0.9099	8	0.0328	9	0.7885	5	4.0290	3	25
7	250	0.8463	6	0.0557	6	0.8688	8	0.0872	13	33
8	300	0.8056	4	0.0703	4	0.6451	3	19.213	2	13
9	350	0.9112	9	0.0323	10	0.7799	4	0.5836	8	31
10	400	0.9493	14	0.0187	14	0.9508	12	0.1578	10	50
11	450	0.9477	13	0.0190	13	0.9513	13	0.8288	6	45
12	500	0.9047	7	0.0346	8	0.8871	10	58.594	1	26
13	550	0.9443	12	0.0210	12	0.9392	11	0.0363	14	49
14	600	0.9415	11	0.0212	11	0.8510	7	0.7892	7	36

It can be seen from the results of the hybrid GA-ANN model, that when the population size of the model is increased, the coefficient of determination R^2 of the model will often increase and the mean square error of the MSE response will decrease. However, not all models follow this principle, so it is necessary to rank for the criteria of coefficient of determination R^2 as well as the corresponding mean square error of the MSE model (proposed by Zorlu et al., 2008) has been applied, and the optimal value of population size can be selected for the hybrid GA-ANN model in this study. From the results shown in Table 4, choose the optimal value of population size (pops) for the hybrid GA-ANN model as pops=400. In case of pops=400, the model with the values of the coefficient of determination R^2 as well as the mean square error MSE achieves the most optimal level of Total rank=50 with R^2 =0.9493 and MSE=0.0187 with the training datasets and R^2 =0.9508 and MSE=0.1578 with testing datasets.

Thus, the hybrid GA-ANN model was determined with optimal parameters, including optimal population size pops=400; the value of iterations Ge=500; TolFun= 10^{-8} with the optimal parameters of the artificial neural network ANN model, including TANSIG transfer function; there is a hidden layer with the number of neurons in the hidden layer N=5.

4. Assessing models for calculating and predicting tunnel face area after blasting

Proceed to use the K-fold cross-validation technique (Diamantidis et al. 2000) to evaluate the performance of models. In this technique, the data is divided into K parts, of which (K - 1) part is used for training, building the model and one part is used for testing models. With 136 initial data, divide this data file into 5 random parts, of which 4 parts are for training and 1 part is for testing models. To choose the most accurate model, based on the coefficient of determination R^2 and the mean square error MSE of each model. However, because the values of the coefficient of determination R^2 and the mean squared error of the models MSE, respectively have very small differences, therefore, it is recommended to use the ranking of models to the above R^2 and MSE values each training dataset and test dataset. The following results are obtained in Table 5.

Tab. 5. Rating for models different

Method	Model	Training				Testing				Sum Rank
		R ²	Rank	MSE	Rank	R ²	Rank	MSE	Rank	
ANN	1	0.9484	5	0.0189	4	0.9015	4	0.0338	6	19
	2	0.9352	2	0.0189	4	0.8429	2	0.0595	2	10
	3	0.9490	6	0.0188	5	0.9194	6	0.0284	10	27

	4	0.9519	8	0.0168	7	0.9090	5	0.0463	3	23
	5	0.9480	4	0.02	3	0.9288	12	0.0224	13	32
GA-ANN	1	0.9433	3	0.0213	2	0.9197	7	0.0300	9	21
	2	0.9541	11	0.016	8	0.8794	3	0.0459	4	26
	3	0.9562	14	0.0158	9	0.9268	11	0.0255	12	46
	4	0.9562	15	0.0156	10	0.9401	14	0.0302	8	47
	5	0.9141	1	0.0324	1	0.6913	1	0.0991	1	4

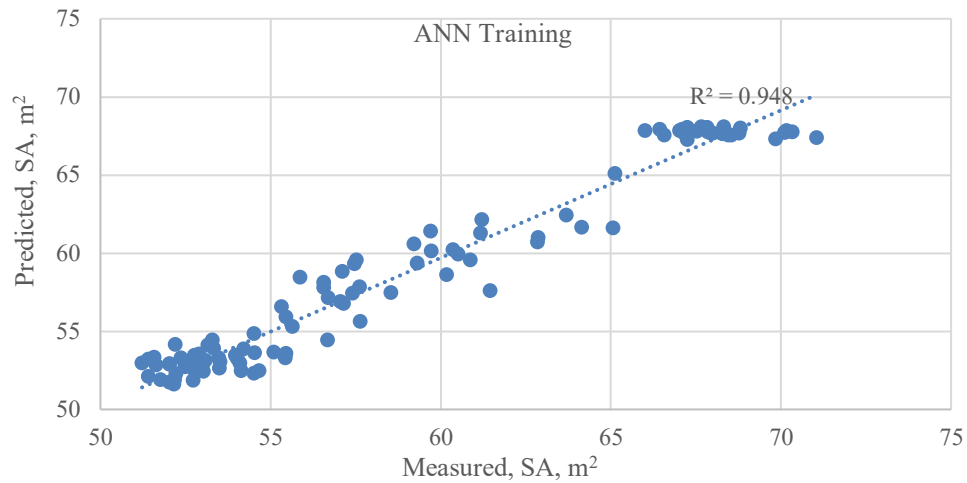


Fig. 10. Measured and predicted the tunnel face area after blasting SA obtained through optimal ANN model for training dataset

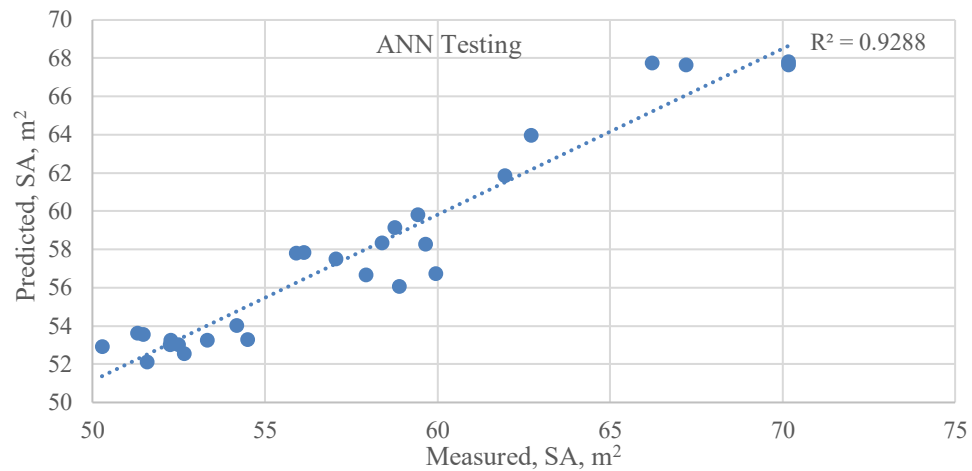


Fig. 11. Measured and predicted SA obtained via the ANN optimal model for testing datasets

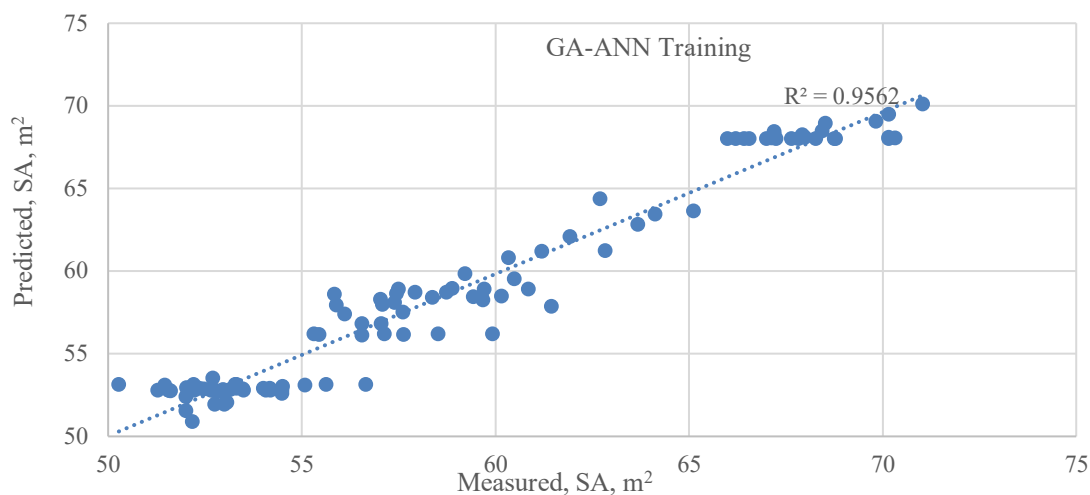


Fig. 12. Measured and predicted SA obtained via the GA-ANN optimal model for training datasets

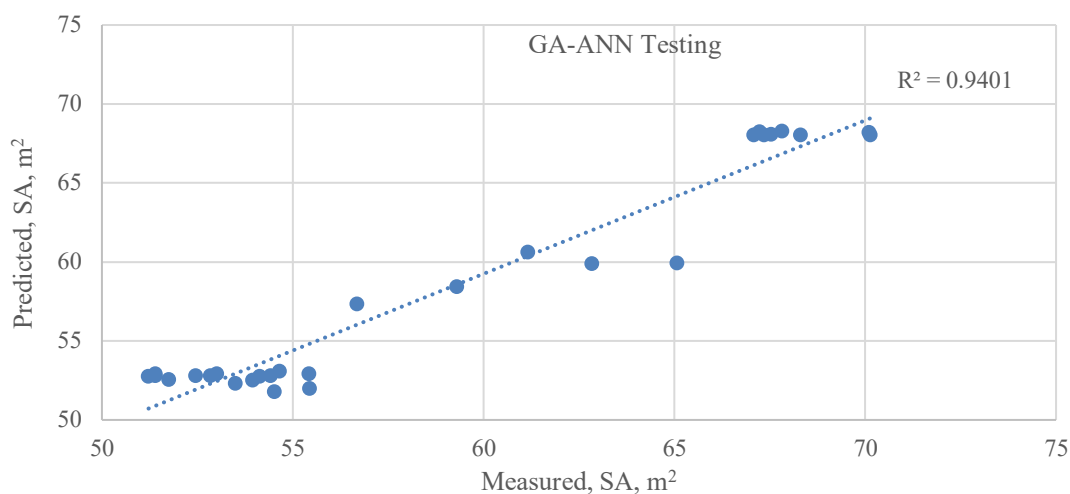


Fig. 13. Measured and predicted SA obtained via the GA-ANN optimal model for testing datasets

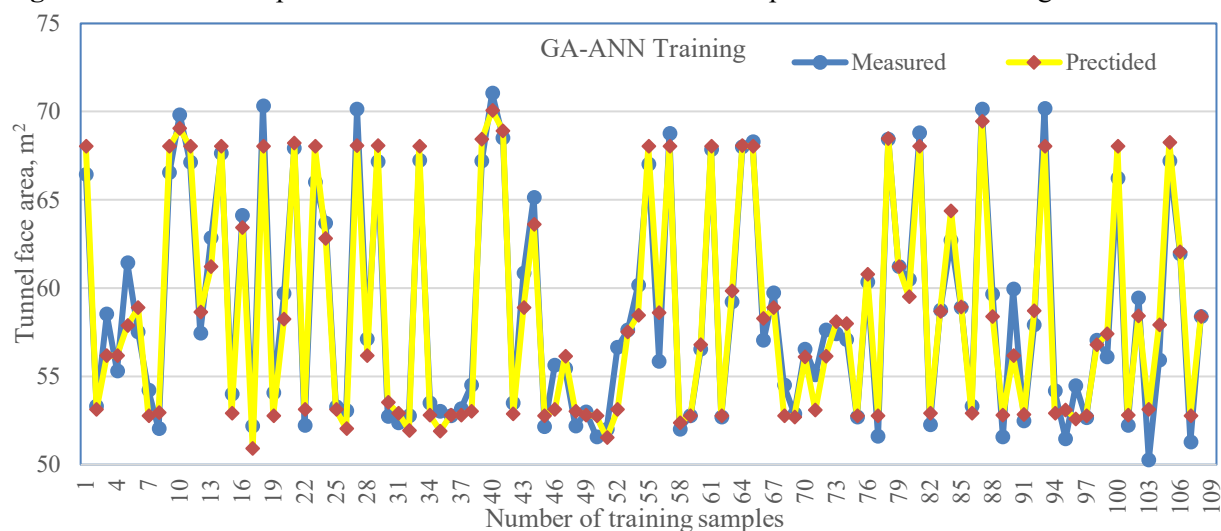


Fig. 14. Comparison between measured and predicted the SA for different training datasets in GA-ANN optimal model

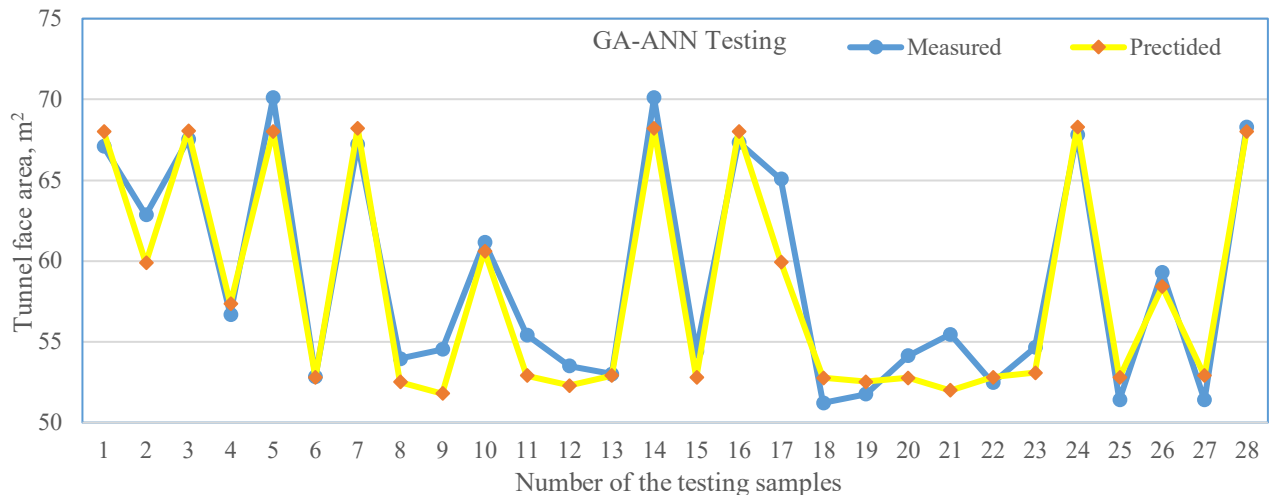


Fig. 15. Comparison between measured and predicted the SA for different testing datasets in GA-ANN optimal model

Based on the results obtained from models using different algorithms (Figures 10-15 and Table 5), the following observations can be made:

- The hybrid GA-ANN model (genetic algorithm combined with artificial neural network) demonstrates high performance and accuracy, with $R^2_{\text{train}}=0.9562$, $R^2_{\text{testing}}=0.94$ and $\text{MSE}_{\text{training}}=0.0156$, $\text{MSE}_{\text{testing}}=0.0302$; The ANN model shows lower performance (lower model accuracy) with $R^2_{\text{training}}=0.948$, $R^2_{\text{testing}}=0.9288$ and $\text{MSE}_{\text{training}}=0.02$, $\text{MSE}_{\text{testing}}=0.0224$;

- When using random data, the model results can vary depending on the size and characteristics of the database used for building, training, and testing. Specifically, for the hybrid GA-ANN model, the population size is a key parameter that must be optimized for each specific model;

- Hybrid models (GA-ANN) improve the accuracy of the results. However, the processing time increases proportionally to the improved accuracy. In the GA-ANN hybrid model, where the genetic algorithm (GA) optimizes the ANN model, the average processing time for a model with the same input dataset was 3862.65 seconds in this paper.

5. Conclusion

The area of the tunnel face after blasting is a key indicator of blasting effectiveness and rock fragmentation in tunnel construction. Currently, estimations of this area rely on geological conditions at the tunnel site, tunnel parameters like the planned face area and cross-sectional shape, borehole characteristics, and the explosives used. This study developed and presents an artificial neural network (ANN) model and a hybrid genetic algorithm-artificial neural network (GA-ANN) model, using 136 datasets of parameters affecting the tunnel face area after blasting. These datasets were collected during the construction of the Deo Ca tunnel in Phu Yen, Vietnam. By comparing the models' calculated results with actual measurements from the tunnel construction, the paper can draw the following conclusions:

- An artificial neural network (ANN) model, featuring a 4x5x1 structure (4 neurons in the input layer, 5 in the hidden layer, and 1 in the output layer), can accurately predict the tunnel face area after blasting.

- Hybrid models, which combine artificial neural networks (ANNs) with optimization algorithms like genetic algorithms (GAs), require careful selection of optimal algorithm parameters for effective model construction. For GA optimization, an important parameter to control is population size;

- Developing and using hybrid models, such as GA-ANN combinations, has led to highly accurate predictions of tunnel face area after blasting. The GA-ANN model can also adjust controllable parameters to enhance blasting efficiency in underground construction. However, these hybrid models demand more powerful computer hardware and longer processing times compared to ANN models alone.

Acknowledgment

This research is supported by Vietnam National Coal and Mineral Industries Holding Corporation Limited (Vinacomin) under grant number: **KC.01.Đ06-25/21-25** and Hanoi University of Mining and Geology.

References

- Alsarraf A, Moayedi H, Rashid ASA, Muazu MA, Shahsavari A (2019) Application of PSO-ANN modelling for predicting the exergetic performance of a building integrated photovoltaic/thermal system. *Eng Comput* 36:1–14.
- Armaghani, D.J., Hajihassani, M., Mohamad, E.T., Marto, A., Noorani, S.A., (2014). Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arabian J. Geosci.* 7 (12), 5383–5396.
- Armaghani DJ, Shoib R, Faizi K, Rashid ASA (2017) Developing a hybrid PSO-ANN model for estimating the ultimate bearing capacity of rock-socketed piles. *Neural Comput Appl* 28:391–405.
- Chi T. N., Do N. A., Pham V. V., Nguyen P. T., Gospodarikov A., Prediction of blast-induced the area of the tunnel face in underground excavations using fuzzy set theory ANFIS and artificial neural network ANN. *International Journal of GEOMATE*, 2022, 23(95), pp. 136–143.
- Danial JA, Shoib RSN, Faizi K, Rashid ASA., (2015). Developing a hybrid PSO-ANN model for estimating the ultimate bearing capacity of rock-socketed piles. *Neural Comput & Applic.* DOI 10.1007/s00521-015-2072-z.
- Dey, K., Murthy, V.M.S.R., (2012). Prediction of blast induced over break from un-controlled burn-cut blasting in tunnel driven through medium rock class. *Tunn. Undergr. Space Technol.* 28, 49–56.
- Esmaili, M., Osanloo, M., Rashidinejad, F., Aghajani, A.B., Taji, M., (2014). Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting. *Eng. Comput.* 30 (4), 549–558.
- Gordan, B., Armaghani, D.J., Hajihassani, M., Monjezi, M., (2016). Prediction of seismic slope stability through combination of particle swarm optimization and neural network. *Eng. Comput.* 32 (1), 85–97.
- Hajihassani, M., Armaghani, D.J., Sohaei, H., Tonnizam, E.M., Marto, A., (2014). Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Appl. Acoust.* 80, 57–67.
- Hasanipanah, M., Noorian-Bidgoli, M., Armaghani, D.J., Khamesi, H., (2016a). Feasibility of PSO-ANN model for predicting surface settlement caused by tunneling. *Eng. Comput.* 32 (4), 705–715.
- Hasanipanah, M., Naderi, R., Kashir, J., Noorani, S.A., Qaleh, A.Z.A., (2017a). Prediction of blast-produced ground vibration using particle swarm optimization. *Engineering with Computers* 33 (2), 173–179.
- Holland. (1975). *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence.* University of Michigan Press, Ann Arbor, USA.
- Hecht-Nielsen R (1987) Kolmogorov's mapping neural network existence theorem. In: *Proceedings of the first IEEE international conference on neural networks*, San Diego, CA, USA, pp 11–14.
- Jang, H., Topal, E., (2013). Optimizing over break prediction based on geological parameters comparing multiple regression analysis and artificial neural network. *Tunn. Undergr. Space Technol.* 38, 161–169.
- Jahed Armaghani D, Hajihassani M, Mohamad ET, Marto A, Noorani SA (2014) Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arab J Geosci* 7:5383–5396.
- Koopialipoor, M., Armaghani, D.J., Haghighi, M., Ghaleini, E.N., (2017). A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels. *Bull. Eng. Geol. Environ.* <http://dx.doi.org/10.1007/s10064-017-1116-2>.
- Lawal AI, Kwon S., (2021). Application of artificial intelligence to rock mechanics: An overview. *Journal of Rock Mechanics and Geotechnical Engineering.* 13(1): 248–266.
- Longqi L, Moayedi H, Ahmad SA, Rahman SS, Nguyen H., (2019). Optimizing an ANN model with genetic algorithm (GA) predicting load-settlement behaviours of eco-friendly raft-pile foundation (ERP) system. *Engineering with Computers.* <https://doi.org/10.1007/s00366-019-00767-4>.
- Liu, Y., Hou, S., (2019). Rockburst prediction based on particle swarm optimization and machine learning algorithm. In: *Proceedings of the 3rd international conference. ICITG*, pp. 290–303.

- Nguyen H, Bui XN, Tran QH, Moayedi H., (2019). Predicting blast-induced peak particle velocity using BGAMs, ANN and SVM: a case study at the Nui Beo open-pit coal mine in Vietnam. *Environmental Earth Sciences* 78(15). DOI:10.1007/s12665-019-8491-x.
- Mahtab, M.A., Rossier, K., Kalamaras, G.S., Grasso, P., (1997). Assessment of geological over break for tunnel design and contractual claims. *Int. J. Rock Mech. Min. Sci.* 34 (3–4).
- Moayedi H, Foong LK, Nguyen H, Bui DT, Jusoh WAW, Rashid ASA (2019). Optimizing ANN models with PSO for predicting in short building seismic response. *Eng Comput* 36:1–16.
- Mohamad ET, Faradonbeh RS, Armaghani DJ, Monjezi M, Majid MZA (2017). An optimized ANN model based on genetic algorithm for predicting ripping production. *Neural Comput Appl* 28:393–406.
- Mohsen H, Armaghani DJ, Monjezi M, Mohamad ET, Marto A. (2015). Blast-induced air and ground vibration prediction: a particle swarm optimization-based artificial neural network approach. *Environ Earth Sci*. DOI 10.1007/s12665-015-4274-1.
- Monjezi M, Dehghani H (2008) Evaluation of effect of blasting pattern parameters on back break using neural networks. *Int J Rock Mech Min Sci* 45:1446–1453.
- Mottahedi, A., Sereshki, F., Ataei, M., (2018). Development of overbreak prediction models in drill and blast tunneling using soft computing methods. *Eng. Comput.* 34 (1), 45–58.
- Poli, R., Kennedy, J., Blackwell, T., (2007). Particle swarm optimization an overview. *Swarm Intell.* 1, 33–57.
- Rodríguez del Águila N.M, Benítez-Parejo N., (2011). Simple linear and multivariate regression models. *Allergologia et Immunopathologia.* 39(3), 159-173.
- Shahnazar, A., Rad, H.N., Hasanipanah, M., Tahir, M.M., Armaghani, D.J., Ghorogi, M., (2017). A new developed approach for the prediction of ground vibration using a hybrid PSO-optimized ANFIS-based model. *Environ. Earth Sci.* 76 (15), 527.
- Simpson PK (1990) *Artificial neural system: foundation, paradigms applications and implementations.* Pergamon, New York.
- Whitley, D. (1993a). An executable model of a simple genetic algorithm. In *Foundations of Genetic Algorithms 2*, ed. D. Whitley. Morgan Kaufmann, San Mateo, CA.
- Zorlu K, C. Gokceoglu, F. Ocakoglu, H. A. Nefeslioglu, and S. Acikalin, (2008) “Prediction of uniaxial compressive strength of sandstones using petrography- based models,” *Engineering Geology*, vol. 96, no. 3-4, pp. 141–158, 2008.

