Proceedings of the 9ICEG
9th International Congress on Environmental Geotechnics
25-28 June, 2023 | Chania, Greece
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https://doi.org/10.53243/ICEG2023-251

Rockmass classification to Artificial Intelligent Techniques for solving Environmental issues due to Blasting in Tropically Weathered Rocks

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ABSTRACT

For hard rock excavation, blasting is essential activity for breaking rock masses. Environmental issues such as Flyrock, Ground vibration and Air Over Pressure (AOp) are created due to the blasting. On the other hand, blasting engineer faces challenge due to large size boulders created during primary blasting. Limestone as sedimentary rock and granite, andesite as igneous rocks in tropical region are selected for this study. Each rock type is classified based on the degree of weathering. Limestone is classified into four classes known as W1, W2, W3 and W4. On the other hand, igneous rocks are classified into five classes namely Fresh (F), Slightly Weathered (SW), Moderately Weathered (MW), Highly Weathered (HW) and Completely Weathered (CW). During last decade blast performance is predicted using Artificial Intelligence (AI) techniques with in put parameters based on blast design, rock mass and explosives. Hybrid models with artificial neural network (ANN) performed better as compared to ANN models. For prediction of flyrock, extreme learning machine (ELM) optimized by biogeography-based optimization (BBO) -ELM BBO model; particle swarm optimization (PSO)-ELM model; PSO-ANN model; hybrid models including Harris Hawks optimization-based Multilayer perception (MLP) (known as HHO-MLP) and whale optimization algorithm-based MLP (known as WOA-MLP) are compared. For prediction of AOp, a fuzzy Delphi method (FDM) with two decision-tree algorithms, namely extreme gradient boosting tree (XGBoost-tree), random forest (RF), genetic programming (GP) are compared. For prediction of ground vibration, hybrid extreme learning machines (ELMs) with the grasshopper optimization algorithm (GOA) and Harris hawk's optimization (HHO) are compared.

Keywords: Air over pressure (AOp), Artificial neural network (ANN), Extreme learning Machine (ELM), Flyrock, Ground vibration, Particle swarm optimization (PSO).

1 INTRODUCTION

Rockmass Classification (RMC) systems have been evolved for the last century in various areas such as tunnelling, slope stability, foundation, excavatability, rippeability to identify the rock mass behaviour. These systems are useful to comprehend and solve various geotechnical issues. Tunnel support rock mass classification system was established considering shear zone, ground condition and rate of excavation in tunnel (Terzaghi,1946). RMC based on GSI was advanced for tropically weathered limestone in Thailand (Bhatawdekar et al., 2017). RMC for blastability was developed considering environmental issues due to blasting, throw and size of muck profile, blast design and powder factor. Such rock mass classification system provides information on the range of rock strength, rock mass properties, joint condition, joint filling, discontinuities in rock, rock quality, and rock weathering parameter.

The variation in temperature as well as heavy rainfall changes the properties of rock mass. In tropical climate, there is a large variation in temperature and substantial amount of rainfall from 1500 to 2500 mm per annum. The infiltration of water within rock mass further reduces the shear strength due to

development of porewater pressure. A number of researchers attempted to classify rock mass adopting various parameters like uniaxial compressive strength, point load index, jointing parameters, blastability index, etc. (Azmi et al., 2010; Bakhtavar et al., 2015; Segaetsho, and Zvarivadza, 2017; Fattahi, and Moradi, 2017). Based on geological, geomechanical and blast design parameters, an AI based tool is discussed to control ground vibration, better fragmentation, reduction in flyrock and AOp. This approach shall control the environmental degradation and enhance productivity.

Limestone and igneous rock mass properties are compared (Wedage et al., 2018; Murlidhar, 2020; Bhatawdekar et al., 2020, 2021; Bhatawdekar et al., 2022). Each rock type is classified based on Uniaxial Compressive Strength (UCS), Point Load Index (PLI), Rock density, Rock Quality Designation (RQD), porosity, Geological Strength Index (GSI) and Blastability Index (BI). Rock mass classification system supports selecting most crucial rock mass parameter while designing blast.

The aim of this study is to understand rock mass classification system developed for tropically weathered rocks such as limestone and granite rock. Important rock mass properties useful for the blast design. Artificial intelligent techniques developed for prediction of environmental effects such as flyrock, ground vibration and AOp are also taken into account.

2 DEVELOPMENT OF ROCK MASS CLASSIFICATION FOR BLASTABILITY

In tropically weathered rock it is possible to distinguish rock mass properties with respect to the degree of weathering.

2.1 Comparison of rock mass properties of limestone

Table 1 shows comparison of limestone from Thailand, Cambodia and Sri Lanka which are in tropical climate. Thickness of limestone decreases from W1 to W2, W2 to W3 and W3 to W4. Sri Lanka does not have W1 type limestone. GSI is applied for limestone mine from Thailand. In Sri Lanka, GSI is not suitable method for RMC as most of the limestone is W3 and W4. Rd, UCS and RQD are compared. These are important properties which contribute to the blasting performance.

Table 1*: Comparison of Tropically Weathered Limestone (Bhatawdekar et al.,2021)*

Country	Degree of weathering				Remarks
	W1	W2	W3	W4	
Thailand	1-100m	2-30m	2-20m	1-5m	Thickness of limestone
Cambodia	5-80m	3-25m	4-20m	2-10m	
Sri Lanka	XXX	2-5m	3-8m	5-15m	
Thailand	40-70%	30-60%	20-50%	15-45%	Geological Strength Index (GSI)
Cambodia	Quarry under development				
Sri Lanka	Unsuitable method as most limestone is W3, W4				
Thailand	Rd= 2.5-2.7 g/cc, UCS=77MPa; RQD= 50-90%,				Rock mass properties
Cambodia	Rd= 2.6-2.7g/cc, UCS= 30-85 MPa; RQD=30-85%				
Sri Lanka	Rd= 2.2 -2.5 g/cc, Too brittle, RQD =10-15%				

Table 1 (Continued)*: Comparison of Tropically Weathered Limestone (Bhatawdekar et al.,2021)*

Country	Degree of weathering				Remarks
	W1	W2	W3	W4	
Thailand	Range Nil to 12%, Average (2%) All cavities empty.				Cavities
Cambodia	Range Nil to 14%, Average (4%) 67% cavities filled with clay, one cave identified				
Sri Lanka	As cavities filled with clay and hence not detected.				

Rock mass classification based on GSI at limestone quarry in Thailand is illustrated through figures (Figure 1- 3). Figure 1 shows cross section of limestone quarry with developed five benches. Various degree of weathered limestone is observed at different benches. Figure 2 illustrates blocky limestone

which is mainly present in top benches and seamy / blocky limestone Figure 3 exhibits very blocky limestone and disintegrated limestone.



***Figure 1**: Cross section of five developed benches of limestone quarry in Thailand (Bhatawdekar et al., 2017).*



***Figure 2**: Blocky limestone (Left). Blocky/seamy limestone (Right)*



Figure 3: *Very blocky limestone (Left). Disintegrated limestone (Right)*

2.2 Comparison of rock mass properties of tropically weathered igneous rocks

Table 2 shows comparison of igneous rocks from Tropical region. Thickness of igneous rock for (F) rock is highest and there is decrease in trend of thickness from (SW), (MW), (HW) to (CW) rock. RQD and GSI varies from country to country. Similarly, Rd, UCS and PLI for limestone vary from country to country.

Table 2*: Comparison of igneous rocks from tropical region (Bhatawdekar et al., 2022a)*

Country	**Degree of weathering**					**Remarks**
	(F)	**(SW)**	**(MW)**	**(HW)**	**(CW)**	
Indonesia	80-100m	3- 20 m	1 to 10 m	-	-	Thickness of rock
Thailand	60-80 m	3-12 m	2-5 m	1-2 m	1-2 m	
Cambodia	40-100 m	5-16 m	3-8 m	2 -6 m	1-2 m	
Malaysia	70-100 m	10-25 m	7-12 m	2-8m	1-10m	
Indonesia	RQD 50% to 100%, GSI 40% to 75%					RQD GSI
Thailand	RQD 40% to 83%, GSI 30% to 65%					
Cambodia	RQD 43% to 88%, GSI 35% to 70%					
Malaysia	RQD 25% to 90%, GSI 25% to 75%					
Indonesia	Rd 2.4 to 2.7g/cc, UCS 89 to 107 MPa, PLI 2 to 10 MPa					Rock mass properties Rd = Rock density
Thailand	Rd 2.3 to 2.6 g/cc, UCS 47 to 62 MPa, PLI 0.2 to 7 MPa					
Cambodia	Rd 2.5 to 2.6 g/cc, UCS 43 to 60 MPa, PLI 0.8 to 82 MPa					
Malaysia	Rd 2.2 to 2.7g/cc, UCS 41 to 69 MPa, PLI 0.1 to 9 MPa					

Figure 4 shows geological structures at granite quarry in Malaysia. Horizontal and vertical joint sets are prominent. Left side of figure has fault zone and these joint sets. Right portion of figure shows andesite dyke intruded in granite. These geological features cause challenge while design of blast for good fragmentation and minimize environmental impact due to blasting.

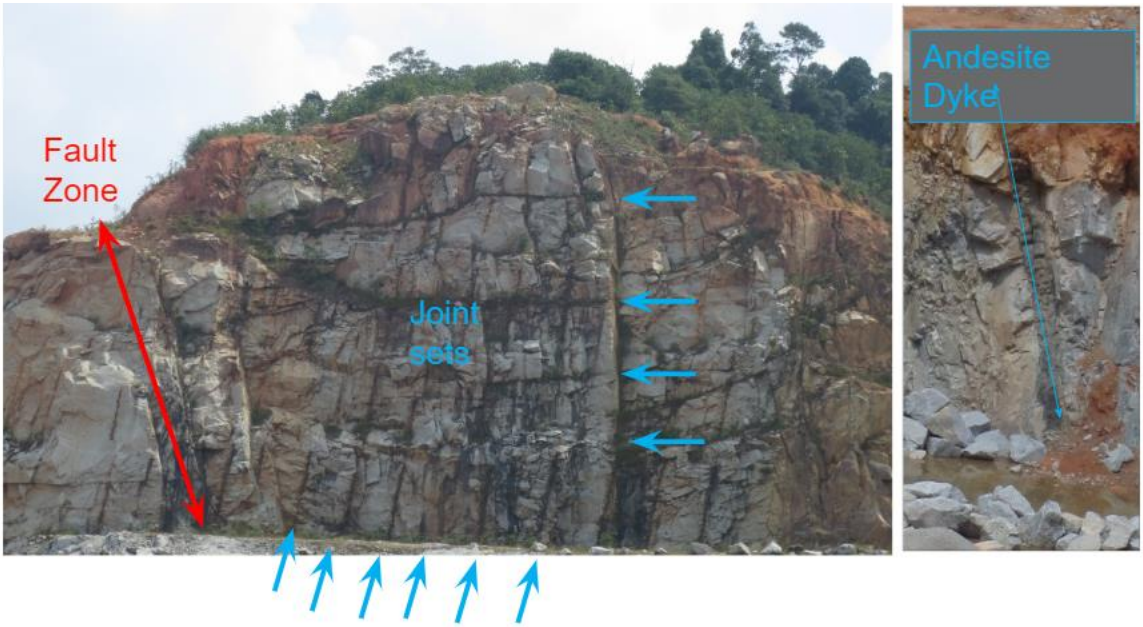

***Figure 4**: Geological structures at granite quarry in Malaysia: Fault zone, horizontal and vertical joint sets at granite quarry (Left). Andesite dyke intrusion in granite (Right) (Murlidhar, 2020).*

2.3 Development of artificial intelligent techniques

During the last century various researchers utilized empirical equations for prediction of environmental issues due to blasting. These equations were based mainly on blast design parameters. Later statistical and numerical models were also tried for prediction of blasting performance with lower accuracy. Artificial intelligent techniques have shown better accuracy (Monjezi et al.,2010; Ghasemi et al., 2014; Koopialipoor et al., ,2019; He et al., 2023).

2.3.1 Artificial neural network

With the inspiration of working of human brain for processing of information, artificial neural network was developed by Donald O. Hebb (1949). Normally, ANN consists of input layer hidden layer and output layers. Sometimes we have more than one hidden layer based on criticality and complex cases. The inputs are received by input layer and passed on to the next layers with error correlation through weightage and final prediction is done by output layer with maximum similarity. Training of neurons is done with the support of activation function. For minimizing loss during back propagation, weights are adjusted. Thus, final output is with minimum loss.
ANN is preferred tool by many researchers as various output related parameters can be accommodated easily. (Esmaeili et al., 2014; Hajihassani et al., 2017; Li et al., 2021; Hasanipanah, et al., 2022). ANN is benchmark tool in AI techniques to compare performance with other models. Various geotechnical engineering issues can be resolved easily. Limitations of ANN are rate of learning is slow and bias for self-stucking to local minima.

2.3.2 Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM), pioneered by Guang-Bin Huang (2014), refers to feedforward neural networks that are applied widely to clustering, classification, sparse approximation compression, regression, and future learning. ELM comprises one or more layers of hidden nodes whose parameters do not need to be tuned. The nodes may be allocated in a totally random way, without any update in future (in other words, they are random projection with nonlinear transforms); they also may be inherited from the ancestors with no modification. The ELM original designer believes that it is capable of producing an excellent generalization performance and learning with significantly higher speed compared to those networks that are trained by means of backpropagation.

There is no need to tune the hidden layers. “Randomness” is known as only one of the ways ELM can be implemented. It also meets the conditions of both ridge regress theory (Hoerl and Kennard, 1970) and neural network generalization theory (Bartlett, 1998). Figure 5 shows input and feature space mapping.

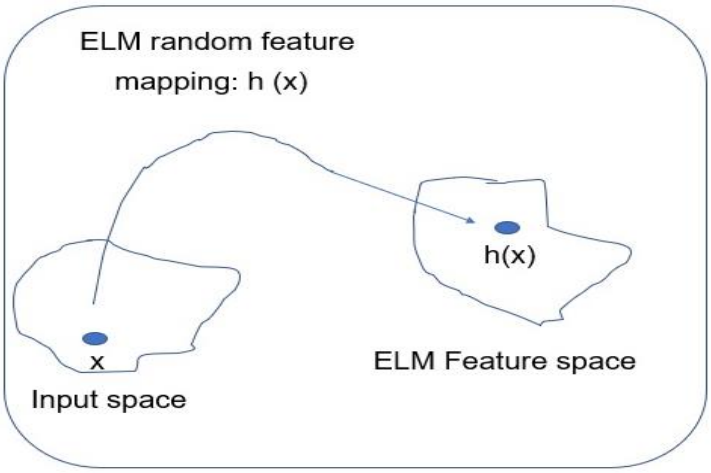

Figure 5*: Input and feature space mapping function together with a definite number of hidden nodes*

Important steps include:
i) Assigning the parameters of the hidden nodes in a random way.
ii) Calculating the hidden layer output matrix.
iii)Calculating the output weights.

“Simple Math is Enough.” ELM is actually a simple algorithm that is free from tuning and works in three steps. ELM enjoys a high speed learning process.

2.3.3 Particle Swarm Optimization (PSO)

Eberhart, Kennedy (1995) observed behaviour of fish and birds and developed evolutionary optimization algorithm known as Particle Swarm Optimization (PSO). The advantage of PSO Algorithm is use of minimum memory resources and provides fast information gathering capability as compared to other optimization algorithm. While seeking excellent positions concurrently, the optimal result is invented on the basis of experiences all swarms. A particle’s velocity and position while in complete motion can be represented as follows:

$$Vnew = (wxV) + B1x(Px - y) + B2(Gx - Y), Ynew = Y + Vnew \quad (1)$$

$$B1 = L1xRand1 \quad (2)$$

$$B2 = L2xRand2 \quad (3)$$

Where Rand1 and Rand2 indicate the random numbers between 0 and 1. Px and Gx represent the personal excellent and global excellent position respectively. L1 and L2 represent factors of learning. Particles current position are represented by Y and V respectively. Particle’s new position and velocity are represented by Ynew and Vnew respectively. The initial coefficient weight is shown as w. Figure 6 shows flowchart of PSO Algorithm.

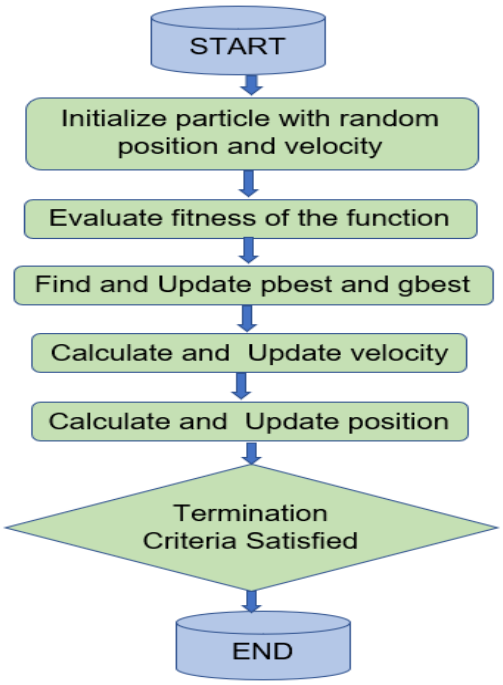

***Figure 6**: Flow chart for PSO algorithm*

The prediction of AOP and ground vibration was carried out with PSO algorithm (Hajihassani et al., 2015 b). To find the adequate number of particles in the swarm (swarm size), a series of sensitivity analyses was applied to the PSO swarm size. While a small swarm may fail to converge to a global solution, a large swarm may lead to delay in the convergence and decrease the efficiency. Thus optimum particle size is found out for swarm to apply PSO model. The results were also compared with ANN and PSO-ANN.

3 DISCUSSION

3.1 Development of Rock Mass Classification for blastability in tropical region:

Various researchers have developed Rock mass classification systems for blastability of tropically weathered limestone and igneous rocks (Bhatawdekar et al., 2021; 2022a). Sedimentary rock can be classified into four classes and igneous rocks in five classes based on the degree of weathering. Table 1 and Table 2 demonstrate that there is wide variation of rock mass properties and also dependent on each country/ site, However, rock mass properties vary linearly from fresh- slightly weathered – moderately weathered tropical rocks. On the other hand, rock mass properties vary exponentially for completely weathered and highly weathered rocks. Hence, it is essential to develop RMC for blastability each site separately. Rock mass classification system supports to design blast based on the degree of weathering. Following two sections show important rock mass properties.

3.1.1 Blastability Index (BI)

BI was developed by Lilly (1986). Each of five parameters of blastability index plays important role on blasting performance. The structural nature of rock mass is important in blast design. Fractured rock mass requiring lower powder factor as compared to blocky rock mass. Closer joint spacing produce finer fragmentation as compared to wider joint spacing and requiring lower energy. Joint plane orientation decides movement direction of blasted stock pile. Horizontal joints require shallow sub-drilling and lower powder factor. Higher density rock needs higher energy for breaking. Lilly had investigated hardness of rock was corelated with compressive strength of rock. Hence, harder rock needs higher energy to break rock. Thus, blastability index and powder factor for each site can be established.

3.1.2 Weathering index (WI)

Weathering index can be calculated by collecting tropically weathered rock samples from each rock face with different degree of weathering. PLI, porosity and water absorption can be determined from each type of rock face. PLI is maximum for fresh tropically weathered rock. Porosity and water absorption are maximum for completely weathered rock. Ratio of each property can be compared with the respective maximum value. The Weathering Index can be determined based on the average of these three ratios for each blasting face.

3.2 Artificial Intelligent techniques

Following section discusses on AI technique used for prediction of blast fragmentation.

3.2.1 PSO-ANN

Most ANN training models, on the other hand, have substantial issues such as a slow learning rate and being stuck in their local minima. Particle swarm optimization (PSO) is an algorithm to optimize the performance of an ANN. In this study, the PSO algorithm was used to improve the performance prediction of the ANN model in order to build a more accurate predictive model for blast fragmentation prediction. PSO is used as an optimization method to minimise a cost function by changing the weights and biases

3.2.2 AI techniques application for blast performance

Table 3 shows various intelligent models used for prediction of blast performance using AI techniques. Simple models for prediction include ANN, ELM, Genetic Programming (GP), Gaussian Process Regression (GPR), M5′, Multi-Layer Perceptron (MLP), Multi Variate Regression analysis (MVRA), Random Forest (RF), SVM. On the other hand, hybrid prediction models are where two algorithms are combined to get the advantages of both models. These models consist of Biogeography based Optimization (BBO), ELM, Genetic Algorithm (GA), Grasshopper Optimization Algorithm (GOA), Harris Hawks optimization (HHO), PSO, Whale optimization algorithm (WOA). Several researchers continue to apply different models. However, ANN is benchmark model to compare performance of these models. Prediction of flyrock, ground vibration due to the blasting and AOP is illustrated with the data sets varying from 125 to 262 data sets. Blast design parameters are d (hole diameter in mm), HD (hole depth in m), BS (burden to spacing ratio), ST (stemming length in m), B (burden in m), CPM (charge per meter in kg), MC (maximum charge per delay in kg, SD (specific drilling in m/cum) and PF (powder factor in kg per ton). DI is distance between seismograph monitoring station and blast measured in m. Rock mass properties include RQD, GSI, BI and JA (Joint Aperture in mm). For flyrock, d, B, S, ST, PF are crucial input parameters. For AOP and ground vibration, MC and DI are critical parameters for control of environmental effect. For each blasting site, impact of input parameters may be different. For flyrock prediction, PSO-ELM, HHO-MLP and SVM were found the best models. For prediction of ground vibration and AOP, best performing models were (GOA-ELM, GPR) and (M5', GA-ANN) respectively.

***Table 3**: AI techniques for prediction of blast performance*

Ref	Models used	Input Parameters	Number of data sets	R^2
		Predicted output- Flyrock		
Murlidhar et al. (2021)	WOA-MLP	d, HD, ST/B, RQD, GSI,	152	0.996
	HHO-MLP	WI, CPM, PF		0.998
	MLP			0.996
	SVM			0.937
	RF			0.933
	Empirical			0.575
Amini et al., (2012)	ANN	d, HD, B, S, PF, SD	245	0.92
	SVM			0.97
		Prediction of ground vibration due to blasting		
Yu et al. (2021)	ELM	BS, HD, ST, PF, MC, DI.	166	0.8928
	GOA-ELM			0.9410

	HHO-ELM			0.9337
Arthur et al. (2022)	GPR	HD, B, D, PF, ST, MC	101	0.9971
	MARS			0.9906
	ELM			0.9915
	BPNN			0.9848
	MVRA			0.6905
	Prediction of AOP due to blasting			
Bhatawdekar et al. (2021)	GP	ST, JA, BI, PF, MC, DI	125	0.8580
	M5'			0.8818
	MLR			0.7810
Tonnizam et al. (2016)	Empirical	MC, DI	76	0.615
	ANN			0.921
	GA-ANN			0.971

4 FUTURE STUDIES

Following further studies can be undertaken:

1.Tropically weathered rocks have variation in rock mass properties, due to which various geotechnical challenges are faced. Further application- slope stability, rippeability, excitability and foundation.
2. Weathering index is newly introduced index. Further tropical region study required.
Optimum number of four to five input parameters need to be established with more trials.
4. Most of the studies are for prediction of individual environmental effect. Further studies need to be established with all input data with multiple outputs including secondary blasting.
5. Large number of data base needs to be established by collaborating with different mines. With cloud computing and applying different AI models, best models can be selected.
6. IOT and sensor technologies need to be adopted for capturing rock mass properties.
7. Use of UAV with digital camera will be useful for flyrock and fragmentation prediction.

5 CONCLUSIONS

1.Tropicall.y weathered limestone is classified into four classes known as W1, W2, W3 and W4. On the other hand, igneous rocks are classified into five classes namely Fresh(F), Slightly Weathered (SW), Moderately Weathered (MW), Highly Weathered (HW) and Completely Weathered (CW).
2.Tropically weathered rocks can be classified based on the variation in rock mass properties such as rock density, strength properties (PLI, UCS), RQD, BI, weathering index.
3. Rock mass classification for tropically weathered rock is useful for initial blast design for minimising environmental impact due to blasting.
4. Various AI Techniques have been developed for prediction of flyrock, ground vibration and AOP due to blasting.
5. As compared to empirical equations, AI Techniques are superior for prediction of environmental issues due to blasting.
6.Rock mass properties (RD, RQD, GSI, WI) for flyrock prediction, (BI, WI) for ground vibration prediction and (JA, BI, WI) for AOP prediction play an important role as input parameters with blast design parameters while application of AI models.
7. As compared to simple AI models such as ANN, ELM, PSO, performance of hybrid models such as PSO-ANN, PSO-ELM, BBO-ELM, HHO-ELM provides better accuracy in prediction.
8. There is need for further research with larger data base of tropically weathered rock mass properties and blasting performance so that future Machine Learning Techniques can be applied for prediction of environmental issues due to blasting.

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