



Optimization of blasting parameters in opencast mine with the help of firefly algorithm and deep neural network

SUNIL KUMAR BISOYI* and BHATU KUMAR PAL

Department of Mining Engineering, National Institute of Technology Rourkela, Rourkela 769008, India
e-mail: sunilbisoyi2022@gmail.com; drbkpal2007@gmail.com

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Abstract. Blasting has been one of the most important contributors of mining since the start of mineral extraction and excavation. Along with fragmentation of the rocks, blasting also produces an excess of energy in the form of heat and vibration. Due to the spread of the vibration, the surrounding environment gets affected. Therefore, this paper aims to minimize the vibration to reduce the impact of ground vibration happening due to the mine blasting. In order to optimize the blasting parameters, a good predictor of such vibration is to be created. Hence, the paper compares a lot of predictors including empirical formulas and ANNs (Artificial Neural Networks). The best performing predictor has been used as the objective function for the optimization of parameters. Among the various optimization methods, the firefly algorithm proved to be a very good optimizer. Therefore, it was used to optimize the field parameters and implemented. The resulting optimized parameters showed a significant reduction in the ground vibration of 14.58%.

Keywords. Artificial neural networks; Back-propagation algorithms; Ground vibration; Peak particle velocity; Firefly algorithm; Meta-heuristic algorithms.

1. Introduction

1.1 Blasting and ground vibration

Being one of the oldest contributors to the world's industrial age, mining has a big role to play in building our modern world. A majority of the blast energy is always lost in the form of heat and noise. During the development of the opencast mines, most of the investment goes towards the blasting of the rocks. The blasting can cost at least 5% of the cost of production during the running of the mine, whereas during the developmental stage, a mine may spend as high as 20% or more of its expenditure towards blasting [1]. The same energy which breaks the rock also sends out weakened shockwaves to the surrounding strata before the energy dissipates. These ground vibrations due to blasting have numerous adverse effects not only on the surrounding environment but also has an impact on humans or human-made structures [2]. As the high energy of the blast is released during blasting, the mechanical wave travels through the ground outwards in every direction from the hole [3]. This vast amount of energy releases an enormous amount of gas and pressure resulting in the development of strain on the surrounding ground strata. This strain crushes the surrounding strata into the powder form, as seen in figure 1, and the subsequent surrounding strata fail due to

tensile strain [4]. The vibration frequency is responsible for damaging the surface structures. When the vibration reaches a structure, the surface structures respond to the vibration by reflecting the wave within the structure. When these vibrations create resonance vibrations, the amplitude of the blast vibration increases, which results in damaging the surface structures/features surrounding the mine area [5]. It is required that blasting parameters should be optimized properly so that the cost of production can be minimized and also the consumption of explosives and minimum ground vibration [6, 7]. The objective of the work is to predict the ground vibration as accurately as possible and to optimize the blasting parameters to reduce the ground vibration using firefly algorithm.

1.2 Literature review

To examine the impact on the surrounding environment due to regular blasting, PPV (Peak Particle Velocity) was chosen for the measurement of vibration due to blasting. It has proven to be a very reliable standard for correlating the damage to the surroundings. From field survey and past studies, it has been seen that scaled distance and charge per delay have been the most influencing parameters of the blast which impacts the ground vibration [8–11]. There have been many attempts to predict the PPV via empirical formulas taking in a small local dataset, but it is hard to

*For correspondence
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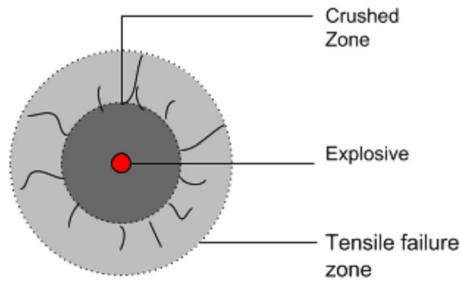


Figure 1. Cross-sectional view of a blast hole.

implement the same universally [10, 12–14]. The usual limitations with this kind of model are that it cannot adopt in different conditions from different sites.

With 220 vibration datasets, Rai proposed a predictor that had a better correlation coefficient than other empirical predictors [15]. One of those common methods of prediction in various regression analysis. Where Agrawal [16] used modified scaled distance regression and Peng *et al* [17] also tried several regression methods among which they found best results using Robust regression. Bisoyi and Pal [18] used various regression analysis, among which the probabilistic Gaussian process regression was the most accurate in predicting the PPV. The work done by different researches are shown below in table 1.

2. Case study

2.1 Mine description

The studies were conducted in the Dongri Buzurg mine (MOIL), which is situated in Bhandara district in the state

of Maharashtra. It is about 120 kms from the nearest city Nagpur. The mine is located in an eastside trending ride rising to +395 MRL. It has a stripping ratio of 1:9. The overall pit slope is about 32-33°. The Bieniawski’s RMR (Rock Mass Rating) [29] in the mine varies between 24 and 70. The mine uses emulsion explosives predominantly with charge factor of 0.4 kg/m³.

2.2 Parameters for the blast

There are eleven parameters that were chosen for the study. Among them the bench parameters which were considered as input parameters are spacing, burden, depth of blast hole, stemming length. These bench parameters have been used by multiple researchers in the field [9, 24, 25]. Parameter like maximum charge per delay and distance from the blasting face were considered of importance by Duvall and Petkof [3], Langefors and Kihlström [14], Singh [30], Monjezi *et al* [31]. There are some additional explosive properties that have been taken into account in order to examine their influence on the ground vibration, such as explosive density, velocity of detonation and charge per blast-hole. The shockwaves of a blast are a mechanical wave which can only travel through a medium. When the medium is changed there is always a part of the shockwave energy which is reflected back. Therefore, the distance of the blast face from the measuring point without changing the medium might be of importance. Hence, the reason why in-land distance is also considered as one of the input parameters in this study. The rock strength parameters and the hole diameter has not been taken into account in prediction because it remained same for this single site and did not contribute to the prediction of the network.

Table 1. Previous studies done with the help of ANN.

Researchers	ANN methods	Layers	Number of datasets	Input parameters	R ²	Error
Khandelwal & Singh [19]	FFBP	13-8-2	150	Di, HD, S, B, D, Q _{max} , BI, Y, P, PW, VOD, CL, Q _h	0.99	MAPE – 4.74
Khandelwal & Singh [20]	FFBP	10-15-2	174	HD, S, B, D, Q _{max} , BI, Y, P, PW, VOD	0.98	MAE – 0.1964
Ragam & Nimaje [21]	FFBP	6-10-1	25	HD, S, B, D, Q _{max} , H	0.99	RMSE – 0.08
Monjezi, Ghafurikalajahi & Bahrami [22]	FFBP	4-10-5-1	162	Q _{max} , D, St, HD	0.95	MAE – 0.002
Gao & Wang [23]	FFBP	2-5-1	10	Q _{max} , D	0.99	MAE – 0.2168
Hajihassani <i>et al</i> [24]	PSO-ANN	9-12-1	62	HD, St, Q _{max} , B, S, RQD, D, H, PF	0.94	MSE – 0.063
Armaghani <i>et al</i> [25]	PSO-ANN	10-15-2	44	Di, HD, Q _{max} , S, B, St, PF, RD, SD, NR	0.93	MAPE – 10.71
Bayat <i>et al</i> [26]	FFBP	4-23-1	154	S, B, D, Q _{max}	0.97	RMSE – 4.38
Iphar <i>et al</i> [27]	ANFIS		44	D, Q _{max}	0.98	
Fisne <i>et al</i> [28]	FIS		33	D, Q _{max}	0.92	
Ghasemi <i>et al</i> [9]	FIS		120	D, Q _{max} , B, S, St, N	0.95	

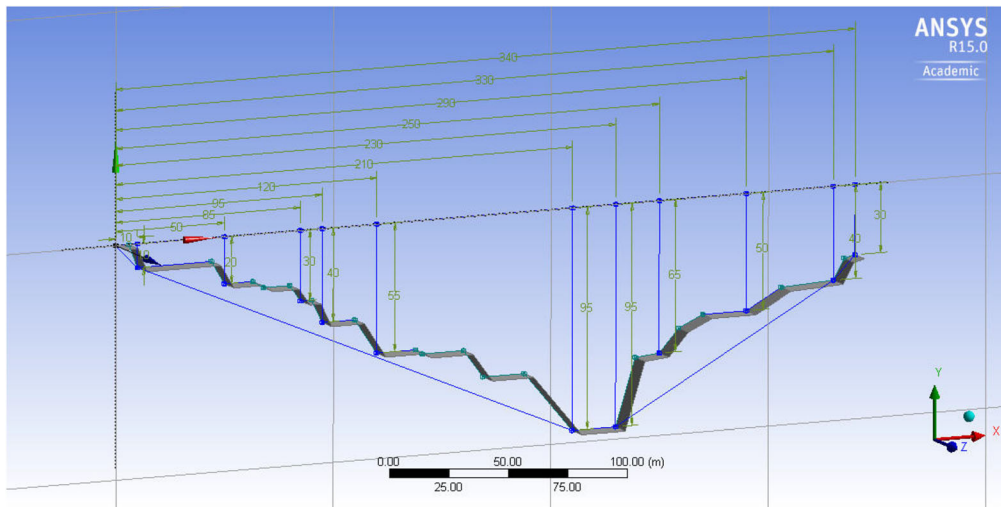


Figure 2. Calculation of in-land distance of shockwave propagation.

The figure 2 shows how the in-land distance has been calculated using the ANSYS 15 software by modelling the opencast mine. The given figure 3 shows the locations of the blast sites and the two monitoring stations from where the data was collected. Along with the PPV reading at the monitoring stations, other blasting parameters (like spacing, burden, distance from the monitoring station, the charge per hole, etc.) were also collected for each of the corresponding blasts. These data will help with the prediction of the PPV.

3. Network training

3.1 Artificial neural networks

The artificial neural network is an expert system which became more popular recently after advancement in computing power. A neural network is loosely based on the neural connections and workings of our own human brain. It consists of a number of nodes and connections which form the network. The connections consist of basic computations that forward the result to the next set of nodes in the next layer. These connections are also known as neurons. The neural network architecture is very simple and capable of categorizing and finding similarities even in a new set of data that has not seen before when trained well.

3.2 Training of the data

Training helps the network to identify patterns and correlations between the input and output parameters. Every connection of the network has a ‘weight’ associated with it. Every node of the network also consists of a numerical value called ‘bias.’ The

output layer compares the output with the target value from the training dataset and calculates the error.

Let’s assume a_j^l is the numeric value stored in a node of the neural network where, l is the layer number and j is the j^{th} neuron of the l^{th} layer.

$$a_j^l = \sigma \left(\sum_k a_k^{l-1} \cdot w_{jk}^l + b_j^l \right) \tag{1}$$

where w_{jk}^l is the weight of the connection which connects from the k^{th} node of $(l-1)^{th}$ layer to the j^{th} node of the l^{th} layer, and b_j^l is the bias associated with the j^{th} neuron of the l^{th} layer [32].

The actual learning of any neural network occurs from a cost function, which can be defined as the error of the network in predicting the target. The cost function decides the amount of adjustment to be applied in each connection. The cost function is defined as follows

$$C_x = \frac{1}{2} \|y - a^L\|^2 = \frac{1}{2} \sum_j (y_j - a_j^L)^2 \tag{2}$$

where L represents the number of layers in the network, y is the target data, and C_x is the cost function for a single training dataset. Basically, C_x is the squared error in a single training data and the complete cost function C is $\frac{1}{n} \sum_x C_x$. Taking this very assumption, it can compute the steepest gradient algorithm needed to tweak the weights and biases for the network connections so as to minimize the cost function. In gradient descent algorithms the steepest descent is calculated with respect to each of the weights and biases and the modifications to their values are done to minimize the cost function.



Figure 3. Locations of blasting sites and monitoring stations.

3.3 Selecting the number of nodes in hidden layers

To select the number of nodes in each of the layers a grid search algorithm was applied to consider all possible combinations of the nodes in each hidden layer. It was decided to consider 3 hidden layers for the neural network. The grid search was done with a combination of 1 to 40 nodes in each of the hidden layers. The combination with best RMSE in validation data is chosen for the network training.

3.4 Sensitivity Analysis of the network

For the sensitivity analysis of network, a comparison needs to be done between the changes in output w.r.t. the changes in the input parameter. Hence, a Gaussian noise had been added at the input end for each of the input parameters and then the trained network is used to predict the output. Doing this for each of the input

parameter we can correlate the changes that happens to output. This way a comparison can be made between the deviation in input and output for every input.

4. Firefly Algorithm

The firefly algorithm [33] used in the study depends on the attractiveness of individual fireflies towards each other. The algorithm depends on three rules: (i) all fireflies are unisexual. Therefore, every firefly is attracted to every other firefly, (ii) attractiveness is proportional to brightness of the individual fireflies. Thus, the dimmer fireflies will move more towards the brighter ones and (iii) the brightness of individual fireflies is based on the objective function.

The attractiveness depends on two factors. One being the brightness and other the distance from each of the fireflies. The brightness is decided using the objective function. The following equation tries to emulate the same.

Table 2. Empirical Predictors.

Predictor Name	PPV from scaled distance	n	k
USBM [10]	$k \left(\frac{D}{\sqrt{Q_{max}}} \right)^{-n}$	0.4265	13.4462
Ambraseys-Hendron [34]	$k \left(\frac{D}{\sqrt[3]{Q_{max}}} \right)^{-n}$	0.3747	40.411
Langefors-Kilhstrom [14]	$k \left(\sqrt{\frac{Q_{max}}{D^{2/3}}} \right)^n$	0.2459	3.7984
Indian Standard [35]	$k \left(\frac{Q_{max}}{D^{2/3}} \right)^{-n}$	0.4917	14.4278

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma r_{ij}^2} (X_j^t - X_i^t) + \alpha_t \epsilon_i^t \quad (3)$$

where t is the iteration number and i denotes update for i^{th} firefly r is the distance, α_t is random number between 0 and 1

and ϵ is a vector of random numbers

$$\beta(r) = \beta_0 e^{-\gamma r_{ij}^2} \quad (4)$$

where β_0 is the attractiveness of firefly at $r = 0$

$$\alpha_t = \alpha_0 \delta^t, 0 < \delta < 1 \quad (5)$$

where α_0 is initial randomness scaling factor and δ is cooling factor.

The above updating equation is an amalgamation of a number of other optimizers with different conditions. Like, when $\beta_0 = 0$, the algorithm becomes a harmonic search algorithm; or in the same case if $e^{-\gamma r_{ij}^2} \rightarrow 0$, the second term in the equation is negligible and the equation reduced to simulated annealing; similarly, in case when $e^{-\gamma r_{ij}^2} \rightarrow 1$ and $\alpha_t = 0$, the equation converts to a type of differential evolution algorithm; when $\gamma = 0$ and X_j^t is replaced by g_{best} (global best for PSO), FA reduces to accelerated PSO. This way it encompasses the advantages of several of the optimization parameters. It also uses nonlinear updating. Therefore, it has higher convergence rate. FA also converges into subdivision and when the subdivisions fail to give good result the entire subdivision population gets rejected. This way the computation eases. It also has

Table 3. Parameters chosen and their range.

Parameters	Range	
Input Parameters	Spacing (m)	2.5–3
	Burden (m)	3–3.5
	Explosive per blast-hole (kgs)	15–34
	Distance from blast site (m)	50–820
	Explosive density (g/cc)	1.15–1.3
	VOD of explosive (m/s)	3048–5791
	Blast hole depth (m)	3–10
	Stemming height (m)	1–4
	Number of holes	24–248
	Maximum charge/delay (kgs)	256–8432
	In-land distance (m)	54.4–844.2
Output Parameter	PPV (mm/s)	0.02–18.82

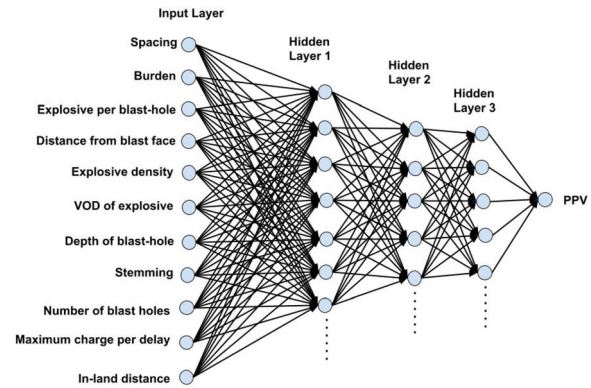


Figure 5. The Neural network layout used in the study.

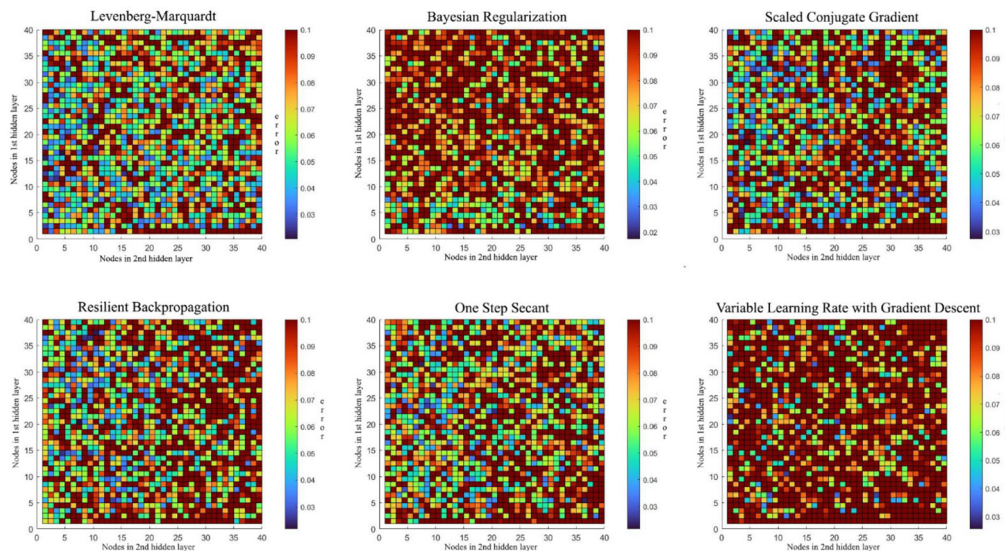


Figure 4. The error in prediction of PPV depending on the number of nodes in each of the hidden layer.

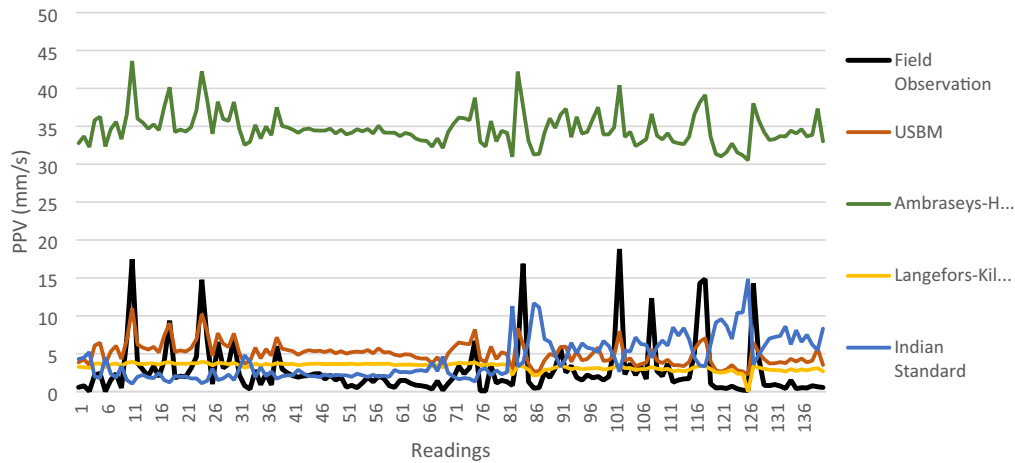


Figure 6. Empirical predictors vs. field observations.

Table 4. Error calculation from the prediction of different models.

	Empirical Predictors			
	USBM	Ambraseys-Hendron	Langefors-Kilstrom	Indian Standard
R ²	0.50	0.61	0.08	0.08
MAD	3.13	31.88	2.34	3.79
MSE	12.40	1021.41	17.84	27.36
RMSE	3.52	31.96	4.22	5.23

controlled randomness as $\alpha_r \in I_i^t$ which can be user defined and controlled.

Considering these many advantages of the FA, it has been chosen as one of the optimization methods for the study. In addition, it also has been compared with a few other optimizers.

5. Conventional Empirical Predictors

This study has taken into account the traditional empirical predictors for comparing the performance of the ANN against the existing predictors in hand. The empirical formulas have proven to be close to the actual measurement of the PPV in the past. All of the empirical formulas chosen in this study rely on two of the input parameters: distance of measuring instrument from the blast site and maximum charge/delay. The below table shows a few of the most popular empirical formulae used for the prediction of PPV. These have proven to be fairly accurate in the past studies.

The ‘n’ and ‘k’ are site constants that are location specific and need to be calculated from the observations done at a certain place. These site constants can be calculated using simple linear regression for each of the equations with the help of the field observations made.

6. Observations

A total of 112 data were collected from the field. Considering the earlier researches, several parameters were chosen, which were collected from the site. The input parameters that were chosen for the study are spacing, burden, explosives per hole, distance from measuring station, explosive density, VOD of explosives, depth of the hole, stemming, number of blast holes, charge per delay and in-land distance.

Along with the above parameters, the PPV of the blasts was collected with the Minimate Series II instrument. The PPV was calculated using the radian, transverse, and vertical PPVs measured in the instrument to get a single scalar value of the PPV. For the calculation of the PPV from the empirical methods, the site constants were calculated using linear regression (table 2).

6.1 Predictions with different empirical formulas

The empirical formulas in the study use a few variations of scaled distance to predict the peak particle velocity. Scaled distance is the ratio of the distance of the blast site from the monitoring station and the square root of the charge per

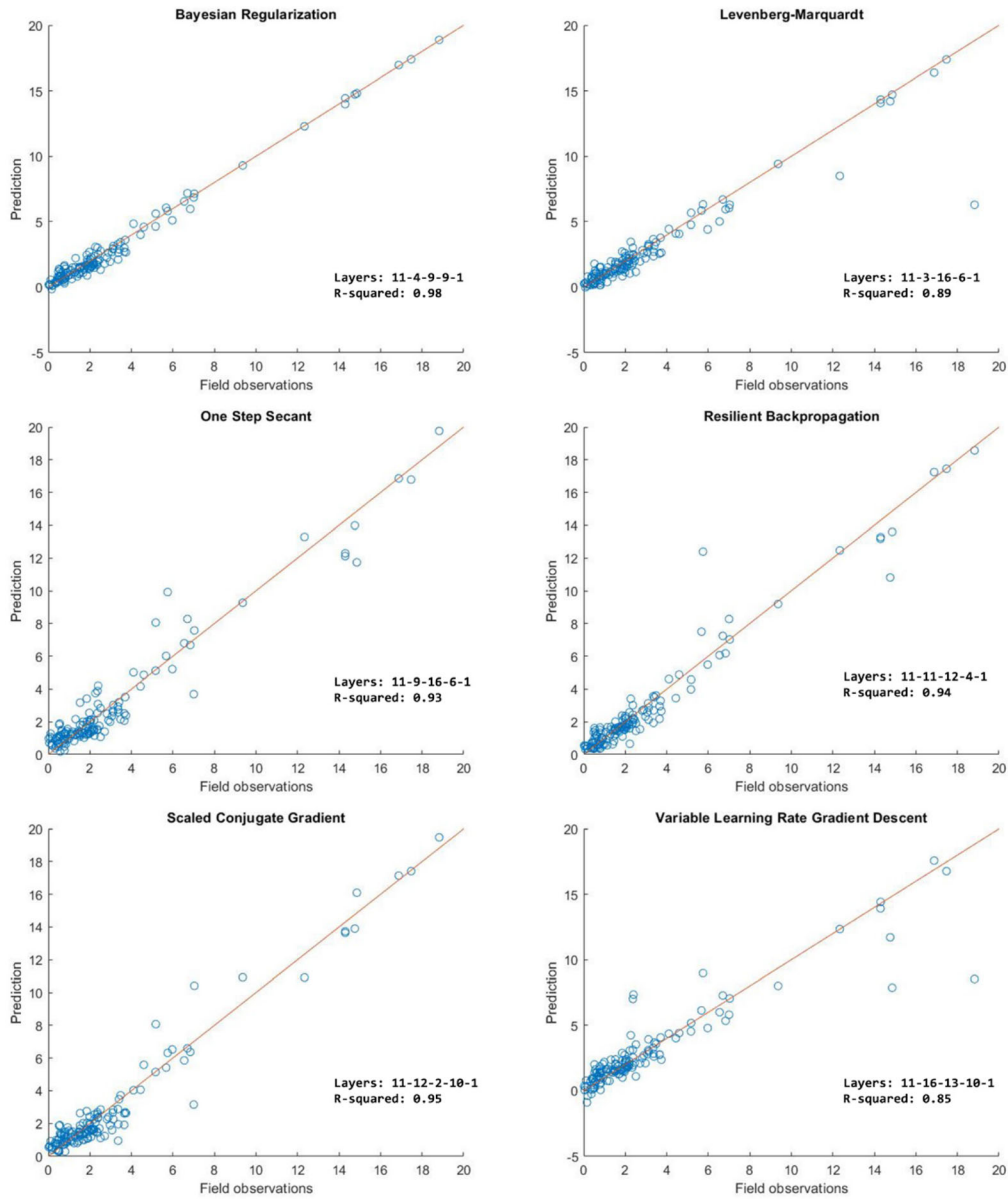


Figure 7. Performance of different ANN algorithms w.r.t. field observations.

Table 5. Coefficient of determination and error in prediction of ANN algorithms.

	ANN algorithm predictions					
	Bayesian Regularization	Levenberg-Marquardt	Scaled Conjugate Gradient	Resilient Back-propagation	One Step Secant	Variable Learning Rate Gradient Descent
R ²	0.98	0.89	0.95	0.94	0.93	0.85
MAE	0.33	0.50	0.57	0.49	0.64	0.69
MSE	0.19	1.49	0.67	0.73	0.83	1.93
RMSE	0.44	1.22	0.82	0.86	0.91	1.39

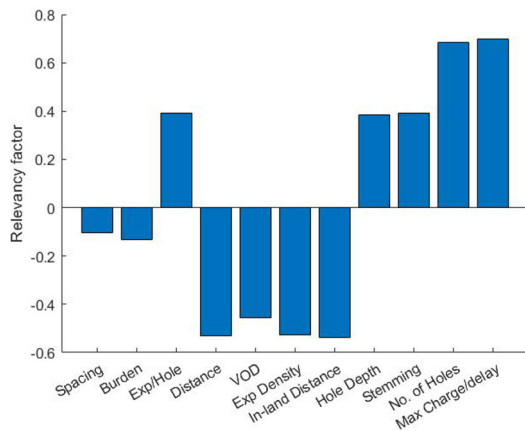


Figure 8. Relevancy factor of the input parameters on the prediction.

delay. So, all of the empirical formulas have used variations of the same basing their formula on their observed data. After calculating site constants, the equations from table 3 had been used to predict the PPV.

6.2 Prediction of blast vibration using ANN

For accurately predicting the ground vibration, the network itself needed to be designed. Because of the difficulty in visualization, out of the three hidden layers only two hidden layers are shown (figure 4) with RMSE value of each respective combination. This operation was repeated for Levenberg-Marquardt algorithms [36], Bayesian-Regularization [37], scaled-conjugate gradient [38], resilient backpropagation [39], one step secant [40] and variable learning rate backpropagation [41]. For each of the algorithms the optimum number of nodes in the hidden layers

were kept respectively. This was to ascertain the best result for each of the algorithms.

The sketch of figure 5 shows the basic architecture of the neural network used in the study. Each of the nodes loosely simulates the work of a neuron, and each of the connection tries and simulates the dendrites as in our own nervous system.

The neural network tool of the software MATLAB 2021b was used to simulate the neural network. The algorithms that have been used for the study are using back-propagation algorithms for training and predicting the PPV.

7. Results and discussion

7.1 Empirical predictions

From figure 6, it seems like the USBM predictor is coming close to predicting the observed PPVs.

By looking at table 4, the predictions of the empirical formulas are not very accurate. The major reliance on scaled distance is a big limitation for such prediction. The Ambraseys-Hendron predictor has a high coefficient of determination but the error is too high because of the offset in prediction.

7.2 Neural network predictions

From figure 7, it can be seen clearly that the performance of the ANN algorithms has shown to be much more accurate than the empirical predictors. With rigorous testing of different network sizes in each of the algorithms, the ANNs were able to predict the PPV with a very good accuracy.

In table 5, it can be seen that the best performing algorithm is Bayesian regularization algorithm with a very good

Table 6. Average blasting parameters before and after optimization.

Blasting Parameters	Lower Bound	Upper Bound	General Parameters (Average)	Optimized Parameters (Average)	Changes in Parameters (%)
Spacing (m)	2	4	2.7	2.5	- 7.4
Burden (m)	2	4	3.0	2.9	- 3.3
Explosive per blast-hole (kgs)	20	50	30.4	28.0	- 7.9
Distance from blast site (m)	50	1200	366.4	366.7	0
Explosive density (g/cc)	5300	5600	5473	5505	+ 0.6
VOD of explosive (m/s)	1.1	1.3	1.28	1.14	- 10.9
Blast hole depth (m)	3	12	9.22	9.74	0
Stemming height (m)	1	4	3.6	3.5	+ 5.6
Number of holes	20	180	94	88	- 2.7
Maximum charge/delay (kgs)	120	500	386.5	361.76	- 6.4
In-land distance (m)	50	1800	389.2	389.2	0

coefficient of determination above 0.98 but all of the neural network algorithms were better than the empirical counterparts.

7.3 Sensitivity analysis

The sensitivity analysis of each of the input parameter on the ground vibration is to be calculated. This can be decided by calculating the relevancy factor [42, 43] of the input variables.

$$RF = \frac{\sum_{i=1}^n (x_{l,i} - \bar{x}_l)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_{l,i} - \bar{x}_l)^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

where $x_{l,i}$ is i^{th} value of the l^{th} input, \bar{x}_l is the average value of l^{th} input, y_i is i^{th} value of predicted output and \bar{y} is average value of predicted output. Figure 8 shows the influence of different parameters on the prediction of the PPV.

7.4 Optimization

The best prediction is given by the Bayesian regularization algorithm. Therefore, it can be used as the function based on which the optimization can be done. Among the several optimization algorithms tested, the firefly algorithm is going to be used as it has multiple advantages compared to the others.

For the optimization the neural network in this study is used as the objective function. As the best performing network was found to be Bayesian Regularization network, it can be used to optimize the parameters. For the optimization, the location was determined for each of the blast and it was kept unchanged but all other parameters were subjected to change within a pre-decided upper and lower bound. The upper and lower bounds were decided according to the requirements of the mine based on the location and amount of rock in the mine wanted to be blasted.

In table 6, the difference in the usual and optimized input parameters can be seen after optimization. With the optimized parameters, a total of 23 blasts were done. The PPV of the the optimized parameters decreased by 14.58% when implemented.

8. Conclusion

From the field observation of 112 unique cases of blasting, several models of predictions were used to predict the peak particle velocity. The artificial neural networks that were used for the studies have proven to be the most accurate in terms of predicting the same. The neural networks far outperform the empirical predictors with Bayesian

regularization algorithms having the best coefficient of determination of 0.98. At the same time the empirical formulas were incapable of attaining that high of an accuracy because of their sole dependence on the scaled distance. A sensitivity analysis was done for the network prediction using relevancy factor and it was seen that maximum charge per delay, number of holes were the most influencing parameters in the prediction. It is also seen that the newly introduced parameter in-land distance does not have much relevance on the prediction outcome. For optimization of the parameters the Firefly algorithm was chosen because of its various advantages, including the computation time and avoiding local minima. With 23 more blast studies with adjusted parameters, there was a considerable reduction of 14.58% in ground vibration during the field testing.

Abbreviations

FFBP	feed-forward back-propagation
PSO	particle swarm optimization
ANFIS	adaptive neuro-fuzzy interference system
Di	hole diameter
HD	hole depth
S	spacing
B	burden
D	distance
Q_{\max}	maximum charge per delay,
BI	blastability index
Y	Young's modulus
P	Poisson's ratio
PW	P-wave velocity
VOD	velocity of detonation
CL	charge length
Q_h	charge per hole
St	stemming length
H	number of holes
N	number of rows
PF	powder factor
RD	rock density
SD	sub-drilling
NR	number of rows
MAPE	mean absolute percentage error
MAE	mean absolute error
RMSE	root mean square error

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Declarations

Conflict of interest The authors have no conflict of interest whatsoever with regard to any of the findings of the study.

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