FedUni ResearchOnline

<https://researchonline.federation.edu.au>

Copyright Notice

This is the post-peer-review, pre-copyedit version of an article published in Geomechanics and Geophysics for Geo-Energy and Geo-Resources. The final authenticated version is available online at:

<https://doi.org/10.1007/s40948-020-00164-y>

Copyright © 2020 Springer Nature Switzerland AG. Part of Springer Nature.

Geomechanics and Geophysics for Geo-Energy and Geo-Resources

OPTIMIZATION OF BLASTING DESIGN IN OPEN PIT LIMESTONE MINES WITH THE AIM OF REDUCING GROUND VIBRATION USING ROBUST TECHNIQUES

--Manuscript Draft--

Manuscript Number:	GGGG-D-19-00147R3
Full Title:	OPTIMIZATION OF BLASTING DESIGN IN OPEN PIT LIMESTONE MINES WITH THE AIM OF REDUCING GROUND VIBRATION USING ROBUST TECHNIQUES
Article Type:	Original Paper
Funding Information:	
Abstract:	<p>Blasting operations create significant problems to residential and other structures located in the close proximity of the mines. Blast vibration is one of the most crucial nuisances of blasting, which should be accurately estimated to minimize its effect. In this paper, an attempt has been made to apply various models to predict ground vibrations due to mine blasting. To fulfill this aim, 112 blast operations were precisely measured and collected in one the limestone mines of Iran. These blast operation data were utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). The input parameters used in this study were burden, spacing, maximum charge per delay, distance from blast face to monitoring point and rock quality designation and output parameter was the PPV. The conventional empirical predictors and multivariate regression analysis were also performed on the same data sets to study the PPV. Accordingly, it was observed that the ANN model is more accurate as compared to the other employed predictors. Moreover, it was also revealed that the most influential parameters on the ground vibration are distance from the blast and maximum charge per delay, whereas the least effective parameters are burden, spacing and rock quality designation (RQD). Finally, in order to minimize PPV, the developed ANN model was used as an objective function for imperialist competitive algorithm (ICA). Eventually, it was found that the ICA algorithm is able to decrease PPV up to 59% by considering burden of 2.9m, spacing of 4.4m and charge per delay of 627Kg.</p>
Corresponding Author:	<p>Masoud Monjezi</p> <p>IRAN, ISLAMIC REPUBLIC OF</p>
Corresponding Author Secondary Information:	
Corresponding Author's Institution:	
Corresponding Author's Secondary Institution:	
First Author:	Afsaneh Rezaeineshat
First Author Secondary Information:	
Order of Authors Secondary Information:	
Order of Authors:	<p>Afsaneh Rezaeineshat</p> <p>Masoud Monjezi, PhD</p> <p>Amirhossein Mehrdanesh</p> <p>Manoj Khandelwal, PhD</p>
Author Comments:	No comments
Response to Reviewers:	<p>Comments for the Author:</p> <p>The paper now reads better. However I still find that authors have not done to improve the abstract except addition of some text at the end (it is too long). The abstract must be very clear and attractive to the readers. Please re-write it and length should be around 300 words</p>

	Response: The abstract has been rewritten and now shortened to make around 300 words.
--	---

[Click here to view linked References](#)

OPTIMIZATION OF BLASTING DESIGN IN OPEN PIT LIMESTONE MINES WITH THE AIM OF REDUCING GROUND VIBRATION USING ROBUST TECHNIQUES **COMPARISON OF EMPIRICAL AND ROBUST TECHNIQUES FOR PREDICTION OF GROUND VIBRATION DUE TO BLASTING IN OPEN PIT LIMESTONE MINES**

Afsaneh Rezaeineshat¹, Masoud Monjezi¹, ~~Afsaneh Rezaeineshat¹~~, Amirhossein Mehrdanesh¹ & Manoj Khandelwal²

1 Faculty of Engineering, Tarbiat Modares University, Tehran, ~~Islamic Republic of~~ Iran

2 School of Science, Engineering and Information Technology, Federation University Australia,

PO Box 663, Ballarat, Victoria 3353, Australia.

Phone: +61 3 5327 9821. Email: m.khandelwal@federation.edu.au

Abstract

Blasting operations create significant problems to residential and other structures located in the close proximity of the mines. Blast vibration is one of the most crucial nuisances of blasting, which should be accurately estimated to minimize its effect. In this paper, an attempt has been made to apply various models to predict ground vibrations due to mine blasting. To fulfill this aim, 112 blast operations were precisely measured and collected in one the limestone mines of Iran. These blast operation data were utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). The input parameters used in this study were burden, spacing, maximum charge per delay, distance from blast face to monitoring point and rock quality designation and output parameter was the PPV. The conventional empirical predictors and multivariate regression analysis were also performed on the same data sets to study the PPV. Accordingly, it was observed that the ANN model is more accurate as compared to the other employed predictors. Moreover, it was also revealed that the most influential parameters on the ground vibration are distance from the blast and maximum charge per delay, whereas the least effective parameters are burden, spacing and rock quality designation (RQD). Finally, in order to minimize PPV, the developed ANN model was used as an objective function for imperialist competitive algorithm (ICA). Eventually, it was found that the ICA algorithm is able to decrease PPV up to 59% by considering burden of 2.9m, spacing of 4.4m and charge per delay of 627Kg. ~~Blasting operations creates significant environmental problems in the vicinity of residential areas and also can cause damage tofor the nearby residential and other structures. Blast vibrations are is~~

one of the most crucial nuisances of blasting which should be accurately estimated accurately and specifically to control and diminished the possible risk of damage to the surrounding structures. In this paper, An attempt has been in this paper to apply various models ground vibration prediction models to predict the blast ground vibrations due to mine blasting. To fulfill this, in one the limestone mines of Iran aim, relevant parameters of 112 blast operations were precisely measured 112 blast operations were precisely monitored and collected relevant blasting parameters were measured in one limestone open pit mine of Iran. Moreover Also, the most significant important ground vibration parameters, such as i.e. burden, spacing, rock quality designation (RQD), maximum explosiv maximum charge used per delay and the distance from the blast face to the blast vibration monitoring point were considered and utilized to construct the artificial neural network (ANN) model to predict the peak particle velocity (PPV). Also, The conventional empirical predictors and multivariate regression analysis were also performed to predict the peak particle velocity (PPV) onfor the siame purposeilar data sets, which were used with the ANN modeling. Accordingly after considering different predictor models, it was foun observed that the ANN model is more accurate as compared to the other employed conventional predictors and multivariate linear regression. Also Moreover, it was revealed that the most influential parameters on the ground vibration are the distance from the blast face to the monitoring point and maximum explosive charge used per delay respectively., w Whereas the least effective parameters ones are burden, spacing and rock quality designation (RQD) respectively. Finally, in order to minimize PPV, developedfor up to by considering.

Keywords: Blasting, Ground Vibration, Artificial Neural Networks, Multivariate Regression, Conventional Empirical Predators.

1. Introduction

Blasting is the process, where explosives are used to fragment the rock mass, so that loading equipment can handle the fragmented rocks. The main objective of blasting is to fragment and displace the rock mass [Mehrdanesh et al, 2018]. Nevertheless, in these operations, a huge amount of explosive energy is not used in actual fragmentation and creates number of blast nuisances, such

1 as blast vibration, airblast, flyrock, backbreak, noise, etc, which can affect the surrounding area [
2 Armaghani et al, 2018; Khandelwal and Singh, 2006; Khandelwal and Singh, 2007; Monjezi et al,
3 2011; Monjezi et al, 2013]. Among these environmental nuisances, ground vibration is considered
4 as one of the most significant blasting effects [Monjezi et al, 2010; Hajihassani et al, 2015;
5 Hasanipanah et al, 2015; Khandelwal and Ranjith, 2017]. High intensity ground vibrations
6 generated due to blasting creates unwanted side effects on the structural integrity and groundwater
7 of the adjacent area [Singh and Singh, 2005; Khandelwal and Singh, 2009]. Hence, precise and
8 reliable estimation of ground vibration is need of the hour to alleviate the blasting environmental
9 problems.

10
11 When explosive material is detonated in a blast-hole, a rapid chemical reaction takes places within
12 a fraction of second and creates very high temperature and pressure. This generated gas pressure
13 crushes the surrounding rock mass of the blast-hole and attenuates very rapidly. The remaining
14 energy transmits to the ground and causes strains to the adjacent rocks [Duvall and Petkof, 1958].
15 The strain waves propagated in the rock medium as the elastic waves, when these stress wave
16 intensity diminishes to the ground level [Dowding and Dowding, 1996; Dowding and Hryciw,
17 1986]. These stress waves are identified as blast induced ground vibration.

18
19 Typically, blast vibrations have two key parameters i.e. peak particle velocity (PPV) and
20 frequency. Number of investigators [Nateghi, 2011; Khandelwal et al, 2011; Khandelwal et al
21 2010] have assumed that blast vibrations can be measured in terms of PPV. During a past few
22 decades, number of different empirical vibration predictors have been proposed by various
23 researchers in order to predict the PPV. However, it was found that these empirical vibration
24 predictors are not proficient to predict the PPV in a precise and reliable manner. Some predictors
25 overestimate the PPV values, and some underestimate, whereas high degree of accuracy is required
26 to predict the PPV to determine blast-safety area. This may be due to consideration of only two
27 affecting factors, i.e. maximum explosive charge used per delay and distance from the blast-face
28 to the monitoring point in these predictors, whereas, it is well known fact that blast vibration is
29 affected by many other controllable and non-controllable factors, like spacing, burden, powder
30 factor and stemming [Monjezi et al, 2016; Armaghani et al, 2018]. Other than empirical vibration
31 predictors, statistical techniques have also been widely applied to predict the PPV [Verma and

Singh, 2011; Hudaverdi, 2012]. However, implementation of these techniques are not trustworthy, if the new available data are different from the original ones [Khandelwal and Singh, 2009; Mohamed, 2011; Dyskin et al, 2018].

Nowadays, various soft computing practices have been comprehensively applied and developed to predict and assess the PPV. Khandelwal and Singh [2006] studied viability of empirical conventional predictors and artificial neural network (ANN) model to evaluate, predict and assess the PPV from 150 blasting events. They found that ANN results are very precise rather than the empirical predictors [Khandelwal and Singh, 2006]. Armaghani et al. [2015] and Iphar et al. [2008] applied the adaptive neuro-fuzzy inference system (ANFIS) to estimate the PPV. Fisne et al. [2011] proposed a fuzzy inference system (FIS) model to evaluate and predict the PPV values monitored at the Akdaglar quarry, Turkey. Hasanipanah et al. [2015] applied another soft computing tool, support vector machine (SVM) to evaluate the PPV values observed at Bakhtiari Dam, Iran. Hajihassani et al. [2015] applied hybrid intelligent soft computing techniques, i.e. particle swarm optimization (PSO)-ANN and imperialism competitive algorithm (ICA)-ANN respectively to study the blast induced ground vibration. Table 1 shows a summary of earlier research done by various researchers to predict the PPV based on input parameters, number of datasets and R^2 values.

In all these studies, it was tried to recognize the most influencing parameters related to ground vibration by using various approaches of conventional (regression analysis), empirical (USBM, Ambaraseys and Indian) and machine learning (ANN) methods.

Table 1 A summary of earlier research done by various researchers to predict the PPV.

Reference	Technique	Input variables	No. of dataset	R^2
Iphar et al. (2008)	ANFIS	DI, MC	44	0.98
Monjezi et al. (2011)	ANN	HD, ST, DI, MC	182	0.95
Khandelwal et al. (2011)	ANN	DI, MC	130	0.92
Mohamed (2011)	ANN, FIS	DI, MC	162	ANN = 0.94 , FIS = 0.90
Fisne et al. (2011)	FIS	DI, MC	33	0.92
Li et al. (2012)	SVM	DI, MC	32	0.89
Mohamadnejad et al. (2012)	SVM, ANN	DI, MC	37	SVM = 0.89, ANN = 0.85
Ghasemi et al. (2013)	FIS	B, S, ST, N, MC, DI	120	0.95
Monjezi et al. (2013)	ANN	MC, DI, TC	20	0.93
Jahed Armaghani et al. (2014)	PSO-ANN	S, B, ST, PF, MC, D, N, RD, SD	44	0.94

Hajihassani et al. (2015)	ICA-ANN	BS, ST, PF, MC, DI, Vp, E	95	0.98
Hasanipanah et al. (2015)	SVM	DI, MC	80	0.96
Dindarloo (2015)	SVM	RD, E, UCS, TS, Js, B, S, HD/B, SC, ST, DPR, DI	100	0.99
Hajihassani et al. (2015)	PSO-ANN	BS, MC, HD, ST, SD, DI, PF, RQD	88	0.89
Jahed Armaghani et al. (2015)	ANFIS	DI, MC	109	0.97
Monjezi et al. (2016)	GEP	DI, MC	35	0.878
Hasanipanah et al. (2017)	CART	DI, MC	86	0.95
Shirani Faradonbeh et al. (2017)	GEP	B, S, ST, D, HD, PF, MC, DI	115	GEP=0.876
Khandelwal et al. (2017)	CART	DI, MC	51	0.92

Burden (B); Spacing (S); hole length (HL); stemming (ST); powder factor (PF); blastability index (B); support vector machine (SVM); maximum charge per delay (MC); rock density (RD); hole diameter (D); hole depth (HD); burden to spacing (BS); number of row (N); particle swarm optimization (PSO); sub-drilling (SD); distance from the blast face (DI); total charge (TC); rock quality designation (RQD); Young's modulus (E); imperialist competitive algorithm (ICA); p-wave velocity (Vp); adaptive neuro-fuzzy inference system (ANFIS); fuzzy inference system (FIS); coefficient of determination (R²); uniaxial compression strength (UCS); tensile strength (TS); joint spacing (Js); hole depth-to-burden ratio (HD/B); specific charge (SC); delay per row (DPR), gene expression programming (GEP)

2. Artificial neural networks (ANN)

ANN is basically resembles the human brain [Trippi and Turban, 1992] and comprises numerous interconnected layers. A computational components known as neurons is existed in each layer. ANN has the capacity to solve non-linear problems very easily. ANN is a robust tool and work on function approximation and feature selection [Simpson, 1990; Kosko, 1992]. Initially training of the ANN network is required from input and corresponding output datasets. There are numerous strategies can be applied to train the neurons, nevertheless feed forward back propagation algorithm has added advantages compared to the other existing methods. Back propagation networks encompasses an input, intermediate and an output layers. Number of neurons in the intermediate layer is based on the problem complexity. A connection weight is principally specified between the existing nodes in each layer, while training. This initial weight would be changed to observe the competence of the model [Neaupane and Achet, 2004; Rahul et al, 2015; Verma and Sirvaiya, 2016].

The model accurateness is considered based on the predicted outputs and the actual measured outputs. Various performance indicators (coefficient of determination (R²), root mean square error (RMSE) and variance account for (VAF) (eqs. 1-3)), are typically use to observe the model performance [Monjezi et al, 2013]:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y - y')^2}{\sum_{i=1}^N (y - \tilde{y})^2} \quad (1)$$

$$VAF = \left[1 - \frac{VAR(y - y')}{VAR(y)} \right] \times 100 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y - y')^2} \quad (3)$$

Where

y – Measured values

y' - Predicted values

$\bar{y}$ – Mean of the y values, and

N – Total number of data.

3. Case Study and Input Selection

A detailed blast vibration study was performed at Alvand Qoly quarry (Figure 1) of Kurdistan Cement Company. The quarry site is situated close to the Bijar city in western Iran. Limestone deposit of pliocene age is the main deposit of the quarry. The quarry consists of horizontal bedding planes in nature. The limestone is medium-hard and has uniaxial compressive strength of nearly 80 MPa and a density of 2450 kg/m³.

Fig 1. Geographical location of Alvand Qoly mine

The quarry is having vertical blast holes with 76 mm diameter in all the benches. The average depth of blast holes are 13.5 m in length with a 1 m sub-drilling and 3.5 m of stemming. Ammonium nitrate and Fuel Oil (ANFO) and emulsion explosive were used in blasting operations to blast the limestone. Non-electric system (detonating cord) was used to detonate the explosive.

4. Collection of data sets

Table 2 depicts the inputs (burden, spacing, rock quality designation (RQD), maximum explosive charge used per delay and the distance from blast-face to the monitoring point) and output parameter (peak particle velocity). The collected data was sorted into training and testing data.

Table 2. Various parameters used to develop the models

	Parameter	Symbol	Mean	Min	Max	Std. Dev
Inputs	Burden (m)	B	3.034	2.5000	3.500	0.3534
	Spacing (m)	S	4.145	3.5000	4.900	0.4485
	Charge Per Delay (Kg)	CPD	1464.760	225.0000	3000.000	805.310
	Rock Quality Designation	RQD	66.312	55.0000	75.000	5.9251
	distance from the blast face	DI	850.182	256.0000	1500.000	332.8471
Output	Peak Particle Velocity	PPV	1.021	0.0300	5.810	1.1215

5. ANN architecture

In this study, a total 112 datasets was used to develop the models. The datasets were sorted into training and testing datasets. Back propagation neural network were used to train the model using 87 datasets. Normalization of input and out data sets were done in the range of -1 to 1 and the network elements (number of layers, neurons, transfer function, etc.) were computed. Training of the network was done until the user specified error is not reached. Among the various models, a back propagation network with an architecture 5-16-1 (No.6), as shown in Fig. 2 was showing the best performance. Fig. 3 illustrates the scatter plot between the predicted and monitored PPV for the training datasets with a R^2 values of 0.9003. From the figure, it can be easily said that the ANN method is capable to predict PPV with the least error.

Fig. 2 Architecture of ANN model

Fig. 3 Correlation between measured and predicted PPV in ANN model (Training accuracy)

Table 3 demonstrates the RMSE, VAF and R^2 values for the various network structures. The best model was chosen based on minimum RMSE and maximum VAF and R^2 among all the models.

~~Among the various models, a back-propagation network with an architecture 5-16-1 (No.6), as shown in Fig. 2 was showing the best performance. Fig. 3 illustrates the scatter plot between the predicted and monitored PPV for the training datasets with a R^2 values of 0.9003. From the figure, it can be easily said that the ANN method is capable to predict PPV with the least error.~~

Fig. 4 shows the comparison chart for the training datasets between measured and predicted PPV values. The figure reveals that the predicted PPV is very closer with the monitored PPV, which clearly establish the ANN capability in anticipating these parameters.

Table 3. RMSE, VAF and R^2 for some of the models

No	Architecture	Hidden activation	Output activation	R^2	RMSE	VAF
1	5-22-1	Logistic	Poslin	0.84	0.45	85
2	5-9-1	Poslin	Tanh	0.71	0.63	72
3	5-3-1	Tanh	Poslin	0.81	0.51	82
4	5-28-1	Exponential	Sine	0.80	0.51	79
5	5-10-1	Sine	Logistic	0.89	0.38	90
6	5-16-1	Tanh	Logistic	0.9003	0.35	93
7	5-10-1	Tanh	Poslin	0.82	0.47	82
8	5-7-1	Exponential	Logistic	0.87	0.39	88
9	5-23-1	Sine	Sine	0.72	0.62	73
10	5-15-1	Sine	Exponential	0.83	0.48	83
11	5-5-1	Poslin	Sine	0.72	0.63	71
12	5-30-1	Tanh	Tanh	0.79	0.52	80
13	5-3-1	Tanh	Poslin	0.81	0.51	82
14	5-22-1	Poslin	Poslin	0.73	0.62	74
15	5-17-1	Logistic	Sine	0.78	0.52	77

Fig. 2 Architecture of ANN model

Fig. 3 Correlation between measured and predicted PPV in ANN model (Training accuracy)

Fig. 4 shows the comparison chart for the training datasets between measured and predicted PPV values. The figure reveals that the predicted PPV is very closer with the monitored PPV, which clearly establish the ANN capability in anticipating these parameters.

Fig. 4 Comparison of predicted and measured PPV in ANN model (Training accuracy)

6. Multivariate Linear Regression (MLR)

Multivariable regression analysis is a subdivision of statistics applying to get the mapping between the input and output parameters. MLR technique is widely used in various branches of engineering and sciences [Gokceoglu and Zorlu, 2004; Grima and Verhoef, 1999]. The Statistica software was used to get the governing relationship between the input and output parameters (Eqs. 4). Fig. 5 shows the graphs between predicted and monitored PPV using the MLR technique.

$$PPV = 0.0005(CPD) - 0.0023(D) + 0.01(RQD) + 0.1242(B) + 0.1881(S) + 0.4182 \quad (4)$$

Where,

PPV – Peak particle velocity (mm/s),

CPD – Explosive charge used per delay (kg),

D – Distance between blast face to the monitoring point (m),

RQD – Rock quality designation

B – Burden (m), and

S – Spacing (m).

Fig. 5 shows the graphs between predicted and monitored PPV with R^2 0.5429 using the MLR technique. The graph reveals that predicted PPV by MLR is showing wide scattering compared to the measured PPV.

Fig. 5 Correlation between measured and predicted PPV in MLR model

7. Empirical models

Different empirical models have been suggested by the researchers to predict the peak particle velocity. The most common empirical formula are shown in Table 4. These empirical models were used to get the site constants based on the datasets used while training of the ANN model, as shown in Table 5.

Table 4 .Different Empirical Formula for prediction PPV

USBM [Duvall and Fogelson, 1962]	$PPV = \alpha \left(\frac{D}{\sqrt[2]{CPD}} \right)^{-\beta}$
Ambraseys-Hendron [1968]	$PPV = \alpha \left(\frac{D}{\sqrt[3]{CPD}} \right)^{-\beta}$
Indian Standard [1973]	$PPV = \alpha \left(\frac{D}{\sqrt[3]{CPD^2}} \right)^{-\beta}$

Where α and β the site constants, which can be calculated by multiple regression. The calculated site constants values for the various conventional predictor equations are presented in Table 5

Table 5 .Calculated values of site constants.

Model	Result	R ²
USBM	$PPV = 127.2 \left(\frac{D}{\sqrt[2]{CPD}} \right)^{-1.57}$	0.6872
Ambraseys and Hendron	$PPV = 3175.02 \left(\frac{D}{\sqrt[3]{CPD}} \right)^{-2.05}$	0.6568
Indian Standard	$PPV = 11.27 \left(\frac{D}{\sqrt[3]{CPD^2}} \right)^{-1.81}$	0.6991

Figs 6-8 shown the relationship between measured and predicted PPV by different empirical formula. Here, R² values are ranging from 0.6568 to 0.6991, where Indian model is showing highest R² and Ambraseys model is showing lowest R². All the three conventional models have higher R² compared to the MLR model.

Fig. 6 Correlation between measured and predicted PPV with USBM model

Fig. 7 Correlation between measured and predicted PPV with Ambraseys model

Fig. 8 Correlation between measured and predicted PPV with Indian model

8. Models validation Results and Discussion

Evaluation and assessment of the ANN, empirical and regression models was accomplished using 25 new datasets. These new 25 datasets were not used in the models development. Various performance indices RMSE, VAF and R^2 were pursued to validate the models. ~~Table 6 illustrates the calculated values of RMSE, R^2 and VAF for all three different models. Table 6 shows that the ANN model has the best performance capability in the prediction of PPV compared to MLR, USBM, Ambraseys and Indian models.~~ Figs. 9-18 depicts the scatter plot and comparison chart between predicted and monitored PPV. The R^2 , VAF and RMSE between measured and predicted PPV by MLR is 0.7725, 77.244 and 0.542 respectively. The R^2 , VAF and RMSE measured and predicted PPV by conventional predictors are ranging from 0.865 – 0.881, 82.803 – 87.500 and

0.9002 – 1.5725 respectively. The R^2 , VAF and RMSE between measured and predicted PPV by ANN is 0.9788, 97.833 and 0.174 respectively.

Table 6. Calculated validation indices for the ANN, MLR, USBM, Amberaseys and Indian models

Model	RMSE	VAF (%)	R^2	RMSE	VAF (%)	R^2
	Train			Test		
ANN	0.300576	89.99882	0.900251	0.174926	97.88303	0.97882
MLR	0.639791	54.19502	0.542933	0.570465	77.2441	0.772452
USBM	0.967458	68.5668	0.687166	0.946589	86.89025	0.877972
Amberaseys	1.405504	65.01171	0.656792	1.572548	82.89375	0.865553
Indian	1.001381	69.99199	0.699064	0.900209	87.50964	0.881789

Fig. 9 Correlation between measured and predicted PPV with MLR model

Fig. 10 A comparison chart between predicted and measured PPV with MLR model

Fig. 11 Correlation between measured and predicted PPV with USBM model

Fig. 12 Correlation between measured and predicted PPV with Ambraseys model

Fig. 13 Correlation between measured and predicted PPV with Indian model

Fig. 14 A comparison chart between measured and predicted PPV with USBM model

Fig. 15 A comparison chart between predicted and measured PPV with Ambraseys model

Fig. 16 A comparison chart between predicted and measured PPV with Indian model

Fig. 17 Correlation between measured and predicted PPV in ANN model

Fig. 18 A comparison chart between predicted and measured PPV with ANN model

9. Optimization Section Using ICA

Imperialist competitive algorithm (ICA), developed by Atashpaz-Gargari and Lucas (2007) has been used as a global search population-based algorithm in optimization problems. ICA gets started with a set of random initial generated solutions which call countries. In the second step, the best countries are selected as imperialist countries and the rest form the imperialist colonies. This algorithm has three main processes, namely assimilation, revolution, and competition. In the phase of assimilation, colonies are attracted towards the imperialists by the power of cultural, political and social criteria. During revolution, some sudden changes occurred in the countries' positions. The positions of countries are suddenly changing. Assimilation and revolution, create the potential for the colonies to attain a better position compared to that of their respective imperialist and take over the empire. In the competition phase, the imperialists are striving to develop their colony and all empires try to seize the colonies of other empires. It is possible that relying on their power, all imperialists seizes a minimum of one colony of the weakest empire. Consequently, through the competition process, weak empires fall gently and stronger empires increase their power. Triple

mentioned processes iteratively continues until only the strongest empire retain the power and the others fall. Figure 19 shows the flowchart of the imperialist competitive algorithm.

ICA has been extensively used as optimization algorithm to optimize the complex problems (Hosseini and Khaled, 2014). In the Alvand Qoly quarry, ICA can determine the blasting pattern parameters through the optimization process. Different ICA-based models were created with the use of various modifiable parameters. Following the accomplishment of several analyses, the most appropriate ICA parameters were achieved and recorded in Table 6.

Table. 6 Controllable parameters ICA used in the optimization process

<u>number of decade</u>	<u>number of country</u>	<u>number of imperialism</u>
<u>78</u>	<u>112</u>	<u>30</u>

ICA algorithm requires an objective functions which in this study is the developed ANN model obtained from the previous section. In fact, the ANN model has the task of simulating the objective function.

Fig. 19 Imperialist competitive algorithm flowchart.

Eventually, the optimal pattern parameters (the improved version compared to the initial pattern) in order to reduce ground vibration, were obtained by ICA as shown in Table 7. In addition, the

difference percentages of the parameters compared to their mean values are calculated in Table 7. According to the table, the ground vibration was reduced 59% if there are 3% reduction of burden, 6% increment of spacing, 57% reduction of charge per delay. All of the differences percentage were calculated based on mean values of original database. The results of optimization section confirmed that ICA is a powerful optimization technique which is able to minimize ground vibration up to 59% based on the used database. In fact, this technique, due to its powerful, can be used in other optimization problems in engineering fields.

Table 7. The optimal pattern parameters obtained by ICA to reduce ground vibration

<u>Parameter</u>	<u>Original mean value</u>	<u>Obtained by ICA</u>	<u>Difference (%)</u>
<u>B (m)</u>	<u>3</u>	<u>2.9</u>	<u>3, reduction</u>
<u>S (m)</u>	<u>4.14</u>	<u>4.4</u>	<u>6, increment</u>
<u>CPD (Kg)</u>	<u>1464</u>	<u>627</u>	<u>57, reduction</u>
<u>PPV</u>	<u>1</u>	<u>0.41</u>	<u>59, reduction</u>

10. Results and Discussion

Figs. 9-18 show a comparison between predicted PPV by ANN, MLR and conventional predictor equations. Here, prediction by ANN is closer to the measured PPV whereas, prediction by conventional predictors and MLR has wide variation.

The figures revealed that ANN predicted PPV is just overlapping the measured PPV line, whereas widely used vibration predictors show very high level of error. This is due to the fact that they do not take into consideration all the influencing parameters of blast vibration. All the conventional predictors have site specific constants and these are not able to predict the safe charge for even other similar mining conditions. The value of site and attenuation constants also varied as the ground conditions changed. Moreover, these are derived based on only two parameters i.e.

maximum charge per delay and the distance from monitoring point to blast face. These empirical predictors are based on linear relation between scaled distance ($D/\sqrt{CPD}$) and PPV.

Table 68 illustrates the calculated values of RMSE, R^2 and VAF for all three different models. The Table 6-shows that the ANN model has the best performance capability in the prediction of PPV compared to MLR, USBM, Amberaseys and Indian models. The ANN model is showing highest R^2 and VAF compared to the MLR and other conventional models with less RMSE for training and testing data. From the Figs. 9-18 and Table 8, it can be said that prediction capability of ANN is quite remarkable and compares well to the field observations.

Table 86. Calculated validation indices for the ANN, MLR, USBM, Amberaseys and Indian models

<u>Model</u>	<u>RMSE</u>	<u>VAF (%)</u>	<u>R²</u>	<u>RMSE</u>	<u>VAF (%)</u>	<u>R²</u>
	<u>Train</u>			<u>Test</u>		
<u>ANN</u>	<u>0.300576</u>	<u>89.99882</u>	<u>0.900251</u>	<u>0.174926</u>	<u>97.88303</u>	<u>0.97883</u>
<u>MLR</u>	<u>0.639791</u>	<u>54.19502</u>	<u>0.542933</u>	<u>0.570465</u>	<u>77.2441</u>	<u>0.772452</u>
<u>USBM</u>	<u>0.967458</u>	<u>68.5668</u>	<u>0.687166</u>	<u>0.946589</u>	<u>86.89025</u>	<u>0.877972</u>
<u>Amberaseys</u>	<u>1.405504</u>	<u>65.01171</u>	<u>0.656792</u>	<u>1.572548</u>	<u>82.89375</u>	<u>0.865553</u>
<u>Indian</u>	<u>1.001381</u>	<u>69.99199</u>	<u>0.699064</u>	<u>0.900209</u>	<u>87.50964</u>	<u>0.881789</u>

110. Sensitivity analysis

A sensitivity analysis was performed to assess the effects of each input parameters on the PPV. In this study, the relevancy factor (RF) was used to evaluate the degree of influence of each input parameters on PPV [Chen et al, 2014]. Here, it should be noted that higher the absolute value of RF of any input and output variables, the more significant influence of that input in predicting the output's value. The RF values can be calculated as followed:

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

Where

$x_{l,i}$ – i^{th} value of the l^{th} input variable,
 $\bar{x}_l$ – Average value of the l^{th} input variable,
 y_i – i^{th} value of the predicted output, and
 $\bar{y}$ – Average value of the predicted output.

Fig. 19-20 shows the RF values of each input parameters against the PPV prediction. From the figure, it can be observed that the DI and CPD are the most effective parameters on the PPV prediction, whereas B, S and RQD are the least effective parameters, respectively in this regard.

Fig. 19-20 Sensitivity analysis of the input parameters

12. Conclusions

In the present paper, ANN, empirical models and regression analysis were performed to evaluate and predict the PPV as well as to find the effect of various blast design parameters on the ground vibration. For this study, a database was developed from Alvand-Qoly quarry of northwest Iran. Initially, superiority of different models were investigated from which competence of the neural network modeling was explored. According to outcomes of the application of the network modeling, it is concluded that the most influential parameters on ground vibration are the distance from blast-face to the monitoring point and maximum explosive charge used per delay, respectively and the least effective ones are burden, spacing and rock quality designation (RQD)

respectively. In the last phase of this paper with name of optimization, ICA technique was used to minimize PPV where the developed ANN model was considered as the objective function. Various effective parameters of ICA were identified and utilized in optimizing process. The results of ICA showed that this optimization approach is able to minimize PPV till 59% compared to its mean value. This can be occurred when burden is 2.9m (3% reduction), spacing is 4.4m (6% increment), and charge per delay is 627 Kg (57% reduction). The results of this study can be used for similar conditions and the same model inputs and their ranges.

References:

1. Ambraseys N (1968) Rock Mechanics in Engineering Practice. John Wiley & Sons, NJ United States
2. Armaghani DJ, Faradonbeh RS, Rezaei H, Rashid ASA, Amnieh HB (2018) Settlement prediction of the rock-socketed piles through a new technique based on gene expression programming. Neural Computing and Applications 29 (11):1115-1125
3. Armaghani DJ, Hajihassani M, Mohamad ET, Marto A, Noorani S (2014) Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. Arabian Journal of Geosciences 7 (12):5383-5396
4. Dindarloo SR (2015) Prediction of blast-induced ground vibrations via genetic programming. International Journal of Mining Science and Technology 25 (6):1011-1015
5. Armaghani DJ, Hasanipanah M, Amnieh HB, Mohamad ET (2018) Feasibility of ICA in approximating ground vibration resulting from mine blasting. Neural Computing and Applications 29 (9):457-465
6. Armaghani DJ, Momeni E, Abad SVANK, Khandelwal M (2015) Feasibility of ANFIS model for prediction of ground vibrations resulting from quarry blasting. Environmental Earth Sciences 74 (4):2845-2860
7. Atashpaz-Gargari E., Lucas C., 2007, Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition, 2007 IEEE Congress on Evolutionary Computation, Singapore, 4661-4667.
- 6.8. Attewell P, Farmer I, Haslam D (1965) Prediction of ground vibration parameters from major quarry blasts. Mining and Minerals Eng:621-626

- 7.9. Bureau of Indian Standard (1973). Criteria for safety and design of structures subjected to underground blast.
- 8.10. Chen G, Fu K, Liang Z, Sema T, Li C, Tontiwachwuthikul P, Idem R (2014) The genetic algorithm based back propagation neural network for MMP prediction in CO₂-EOR process. Fuel 126:202-212
- 9.11. Dowding CH, Dowding C (1996) Construction vibrations, vol 81. Prentice Hall Upper Saddle River, NJ,
- 10.12. Dowding CH, Hryciw RD (1986) A laboratory study of blast densification of saturated sand. Journal of Geotechnical Engineering 112 (2):187-199
- 11.13. Duvall WI, Fogelson DE (1962) Review of criteria for estimating damage to residences from blasting vibrations. US Department of the Interior, Bureau of Mines,
- 12.14. Duvall WI, Petkof B (1958) Spherical propagation of explosion-generated strain pulses in rock. Bureau of Mines,
15. Dyskin, A.V., Basarir, H., Doherty, J. et al. Geomech. Geophys. Geo-energ. Geo-resour. (2018) 4: 235. <https://doi.org/10.1007/s40948-018-0086-6>
- 13.16. Faradonbeh RS, Monjezi M (2017) Prediction and minimization of blast-induced ground vibration using two robust meta-heuristic algorithms. Engineering with Computers 33 (4):835-851
- 14.17. Fişne A, Kuzu C, Hüdaverdi T (2011) Prediction of environmental impacts of quarry blasting operation using fuzzy logic. Environmental monitoring and assessment 174 (1-4):461-470
- 15.18. Ghasemi E, Ataei M, Hashemolhosseini H (2013) Development of a fuzzy model for predicting ground vibration caused by rock blasting in surface mining. Journal of Vibration and Control 19 (5):755-770
- 16.19. Gokceoglu C, Zorlu K (2004) A fuzzy model to predict the uniaxial compressive strength and the modulus of elasticity of a problematic rock. Engineering Applications of Artificial Intelligence 17 (1):61-72
- 17.20. Grima MA, Verhoef P (1999) Forecasting rock trencher performance using fuzzy logic. International Journal of Rock Mechanics and Mining Sciences 36 (4):413-432

- 1 [18-21.](#) Hajihassani M, Armaghani DJ, Marto A, Mohamad ET (2015) Ground vibration prediction
2 in quarry blasting through an artificial neural network optimized by imperialist competitive
3 algorithm. Bulletin of Engineering Geology and the Environment 74 (3):873-886
- 4 [19-22.](#) Hajihassani M, Armaghani DJ, Monjezi M, Mohamad ET, Marto A (2015) Blast-induced
5 air and ground vibration prediction: a particle swarm optimization-based artificial neural
6 network approach. Environmental Earth Sciences 74 (4):2799-2817
- 7 [20-23.](#) Hasanipanah M, Faradonbeh RS, Amnieh HB, Armaghani DJ, Monjezi M (2017)
8 Forecasting blast-induced ground vibration developing a CART model. Engineering with
9 Computers 33 (2):307-316
- 10 [24.](#) Hasanipanah M, Monjezi M, Shahnazar A, Armaghani DJ, Farazmand A (2015) Feasibility of
11 indirect determination of blast induced ground vibration based on support vector machine.
12 Measurement 75:289-297
- 13 [25. Hosseini S., Khaled A.A., 2014, A survey on the Imperialist Competitive Algorithm
14 metaheuristic: Implementation in engineering domain and directions for future research,
15 Applied Soft Computing, 24, 1078-1094](#)
- 16 [21-26.](#) Hudaverdi T (2012) Application of multivariate analysis for prediction of blast-induced
17 ground vibrations. Soil Dynamics and Earthquake Engineering 43:300-308
- 18 [22-27.](#) Iphar M, Yavuz M, Ak H (2008) Prediction of ground vibrations resulting from the blasting
19 operations in an open-pit mine by adaptive neuro-fuzzy inference system. Environmental
20 Geology 56 (1):97-107
- 21 [23-28.](#) Khandelwal M, Armaghani DJ, Faradonbeh RS, Yellishetty M, Majid MZA, Monjezi M
22 (2017) Classification and regression tree technique in estimating peak particle velocity caused
23 by blasting. Engineering with Computers 33 (1):45-53
- 24 [24-29.](#) Khandelwal M, Kankar P, Harsha S (2010) Evaluation and prediction of blast induced
25 ground vibration using support vector machine. Mining Science and Technology (China) 20
26 (1):64-70
- 27 [25-30.](#) Khandelwal M, Kumar DL, Yellishetty M (2011) Application of soft computing to predict
28 blast-induced ground vibration. Engineering with Computers 27 (2):117-125
- 29 [26-31.](#) Khandelwal M, Singh T (2006) Prediction of blast induced ground vibrations and
30 frequency in opencast mine: a neural network approach. Journal of sound and vibration 289
31 (4-5):711-725

- 1 [27.32.](#) Khandelwal M, Singh T (2007) Evaluation of blast-induced ground vibration predictors.
2 Soil Dynamics and Earthquake Engineering 27 (2):116-125
- 3 [28.33.](#) Khandelwal M, Singh T (2009) Prediction of blast-induced ground vibration using artificial
4 neural network. International Journal of Rock Mechanics and Mining Sciences 46 (7):1214-
5 1222
- 6 [29.34.](#) Khandelwal, M., Ranjith, P.G. Study of crack propagation in concrete under multiple
7 loading rates by acoustic emission. Geomech. Geophys. Geo-energ. Geo-resour. 3, 393–404
8 (2017) doi:10.1007/s40948-017-0067-1
- 9 [30.35.](#) Kosko B (1992) Neural networks and fuzzy systems: a dynamical systems approach to
10 machine intelligence/book and disk. Vol 1 Prentice hall
- 11 [31.36.](#) Li DT, Yan JL, Zhang L Prediction of blast-induced ground vibration using support vector
12 machine by tunnel excavation. In: Applied Mechanics and Materials, 2012. Trans Tech Publ,
13 pp 1414-1418
- 14 [32.37.](#) Mehrdaneh A, Monjezi M, Sayadi AR (2018) Evaluation of effect of rock mass properties
15 on fragmentation using robust techniques. Engineering with Computers 34 (2):253-260
- 16 [33.38.](#) Mohamadnejad M, Gholami R, Ataei M (2012) Comparison of intelligence science
17 techniques and empirical methods for prediction of blasting vibrations. Tunnelling and
18 Underground Space Technology 28:238-244
- 19 [34.39.](#) Mohamed MT (2011) Performance of fuzzy logic and artificial neural network in
20 prediction of ground and air vibrations. International Journal of Rock Mechanics and Mining
21 Sciences 48 (5):845
- 22 [35.40.](#) Monjezi M, Ahmadi M, Sheikhan M, Bahrami A, Salimi A (2010) Predicting blast-induced
23 ground vibration using various types of neural networks. Soil Dynamics and Earthquake
24 Engineering 30 (11):1233-1236
- 25 [36.41.](#) Monjezi M, Baghestani M, Faradonbeh RS, Saghand MP, Armaghani DJ (2016)
26 Modification and prediction of blast-induced ground vibrations based on both empirical and
27 computational techniques. Engineering with Computers 32 (4):717-728
- 28 [37.42.](#) Monjezi M, Ghafurikalajahi M, Bahrami A (2011) Prediction of blast-induced ground
29 vibration using artificial neural networks. Tunnelling and Underground Space Technology 26
30 (1):46-50

- 1 [38-43.](#) Monjezi M, Hasanipanah M, Khandelwal M (2013) Evaluation and prediction of blast-
2 induced ground vibration at Shur River Dam, Iran, by artificial neural network. Neural
3 Computing and Applications 22 (7-8):1637-1643
- 4 [39-44.](#) Monjezi M, Mehrdanesh A, Malek A, Khandelwal M (2013) Evaluation of effect of blast
5 design parameters on flyrock using artificial neural networks. Neural Computing and
6 Applications 23 (2):349-356
- 7 [40-45.](#) Nateghi R (2011) Prediction of ground vibration level induced by blasting at different rock
8 units. International Journal of Rock Mechanics and Mining Sciences 48 (6):899-908
- 9 [41-46.](#) Neaupane KM, Achet SH (2004) Use of backpropagation neural network for landslide
10 monitoring: a case study in the higher Himalaya. Engineering Geology 74 (3):213-226
- 11 [47.](#) Rahul, Khandelwal, M., Rai, R., Shrivastva B.K., 2015, Evaluation of dump slope stability of
12 a coal mine using artificial neural network, Geomech. Geophys. Geo-energ. Geo-resour. 1: 69-
13 77.
- 14 [42-48.](#) Simpson PK (1990) Artificial neural systems: foundations, paradigms, applications, and
15 implementations. Pergamon,
- 16 [43-49.](#) Singh T, Singh V (2005) An intelligent approach to prediction and control ground vibration
17 in mines. Geotechnical & Geological Engineering 23 (3):249-262
- 18 [44-50.](#) Trippi RR, Turban E (1992) Neural networks in finance and investing: Using artificial
19 intelligence to improve real world performance. McGraw-Hill, Inc.,
- 20 [51.](#) Verma A, Singh T (2011) Intelligent systems for ground vibration measurement: a comparative
21 study. Engineering with Computers 27 (3):225-233
- 22 [45-52.](#) Verma, A.K., Sirvaiya, A. (2016) Comparative analysis of intelligent models for prediction
23 of Langmuir constants for CO₂ adsorption of Gondwana coals in India. Geomech. Geophys.
24 Geo-energ. Geo-resour. 2, 97–109. <https://doi.org/10.1007/s40948-016-0025-3>

Comments for the Author:

The paper now reads better. However I still find that authors have not done to improve the abstract except addition of some text at the end (it is too long). The abstract must be very clear and attractive to the readers. Please re-write it and length should be around 300 words

Response: The abstract has been rewritten and now shortened to make around 300 words.