



# Estimation of blast-induced ground vibrations: a non-linear model based on the imperialist competitive algorithm

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## Abstract

With recent advances in construction and mining, the need for drilling and blasting has been also increasing. Considering the ascending approach in the application of mining process and the need for using of blasting in near occupied region, the safe blasting plays an important role in these areas. In this paper, the application of a non-linear model for estimating ground vibration in terms of peak particle velocity (PPV) is discussed along with including every possible effective factors of rock mass, explosive features, and blast design. The imperialist competitive algorithm (ICA) is employed to find the non-linear estimator model coefficients. According to the calculated statistical error between the estimated and actual values of PPV, ICA-based model demonstrates lower RMSE, VARE, MEDAE, MAE, and VARAE values, while it has higher value of correlation coefficient, compared to the linear model. It is shown that the applicability of ICA-based non-linear model is more promising than traditional multivariate linear regression model.

**Keywords** Ground vibration · PPV · Non-linear model · ICA

## Introduction

The explosive energy that is wasted by ground vibrations can be used for rock fracturing. Strong ground vibrations cause problems for the population living near the site and also deeply influence the integrity of the structures at mine site. Ground vibration caused by the blast induces considerable effects on different structures like buildings, dams, roads, railroads, and natural slopes (Alipour et al. 2011). Avoiding vibration problems entails taking into account different parameters in the design of blasting pattern; among these parameters are physico-mechanical properties of rock mass, characteristics of explosives, and geometrical and timing aspects of the blasting pattern (Hojjat Hosseinzadeh and Aref 2020; Hossaini and Sen 2004; Khandelwal and Singh 2006). For ground vibration estimation, several studies have covered several different linear or non-linear models such as empirical and mathematical models. One of the frequently

used parameters for ground vibration assessment is PPV (Dowding 1985; Dowding and Dowding 1996). Two key parameters (maximum charge per delay and distance from the location of blast) control the empirical equations. There are many empirical models to estimate the PPV (Ambraseys and Hendron 1968; Duvall and Fogelson 1962; Langefors et al. 1958). In many of these models, the PPV has a role to play.

Several parameters affect ground vibration like physico-mechanical properties of rock mass, explosive characteristics, and blast design (Alipour et al. 2012; Samareh et al. 2017). In addition, the design parameters such as delay time, burden, maximum charge per delay, spacing, charge length, decoupling charges, and initiation sequence notably change distribution of the seismic energy. Moreover, different areas in mine or even two ends of a single face have different rock characteristics. Therefore, there is a need to optimize blast design parameters and explosive characteristics on the basis of properties of rock mass such as strength, longitudinal wave velocity, density, porosity, impedance, stress-strain response, and presence of structural discontinuities (Khandelwal and Singh 2006).

Till now, enough investigations have not been done on the relevancy of the geo-mechanic and blast parameters of ground vibration. The complexity of the problem does

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not let model the ground vibration of the blasting under parameters of rock mass, characteristics of explosive, and blast design parameters. A limited number of these models have investigated the effect of rock characteristics, characteristics of explosive, and blast design. These limited researches in this field include the use of artificial intelligence methods in references (Hajihassani et al. 2015; Khandelwal and Singh 2006; Khandelwal and Singh 2009; Yuan et al. 2014).

Kostić et al. developed a neural network model with four main blast parameters as input, namely, total charge, maximum charge per delay, distance from the blast source to the measuring point, and hole depth (Kostić et al. 2013). Also, to evaluate the ground vibrations caused by the blast, the techniques of dimensional analysis and ANN were applied, taking into account the blast design parameters and rock strength (Dehghani and Ataee-pour 2011).

In the recent years, intelligent hybrid computing methods were implemented to predict PPV. Some of these hybrid approaches have been used in Hajihassani et al. 2015, Nguyen et al. 2020, Abbaszadeh Shahri et al. 2021, Qiu et al. 2021, and Fattahi and Hasanipanah 2021.

The use of black-box machine learning models such as artificial neural networks in practical applications in construction project and mining sites is not possible (Alipour et al. 2018; Chehreghani et al. 2011). From the site engineers' point of view, direct clearly formulated models are the most efficient models.

Clearly formulated models are equations that their coefficient should be determined by mathematical method. In order to determine these coefficients, exact mathematical or approximate methods or meta-heuristics can be used. Most of clearly formulated models have been proposed to determine PPV that depend on distance and maximum safe charge for each delay. Fouladgar et al. proposed a cuckoo search algorithm to create a clearly formulated equation for predicting the PPV. The proposed model considered two effective

parameters (Fouladgar et al. 2017). A summary of the PPV estimation models is presented in Table 1.

Here, the authors try to estimate PPV with the help of ICA-based multivariate non-linear model by using relevant parameters of rock mass, characteristics of explosive, and blast design.

This paper is prepared as follows: after the first section in the Introduction, in the second section, the details of the data used in the modeling are presented. In the third section, ICA as research methodology is explained in detail. In the fourth section, PPV estimation by using multivariate ICA-based regression model is presented, and also, the implemented method results are discussed. Finally, in the fifth section, the main remarks are presented as research conclusion.

## Dataset description

One of the subsidiary companies of Coal India Limited at Singrauli, District Sidhi (MP) is selected as our case study. The different ranges of values have been chosen based on accurate field investigations and literature review (Khandelwal and Singh 2006; Singh and Sastry 1986; Singh and Singh 1975).

Many factors determine the nature and intensity of blast that causes ground vibrations. For instance, the effects of the surrounding rock on ground vibration behavior are moderate. Moreover, a key role is played by geological discontinuity in ground vibration transfer (Khandelwal and Singh 2006; Singh and Sastry 1986). The distance from blast face and the spot where the vibration monitoring stuff are located is another effective parameter. A strong effect is induced by blast geometry on control of ground vibration. There are other parameters that can be minimized under control level including charge length, burden, spacing, stemming, hole diameter, length of hole, and sub-drilling. Finally, the type of explosives has an effect on the size of ground vibration (Hossaini and Sen 2004). Database properties used in the

**Table 1** A summary of the PPV estimation models

Model	Type	Reference	Effective factors
Direct clearly formulated models	Exact mathematical model	Duvall and Fogelson 1962, Langefors and Kihlström 1978, and Attewell 2013	Maximum charge per delay and distance
	Approximate models (meta-heuristics)	Khandelwal and Singh 2009	Maximum charge per delay and distance and some other factors
Black-box machine learning models		Fouladgar et al. 2017	Maximum charge per delay and distance
	Artificial intelligence methods	Hajihassani et al. 2015 and Alipour et al. 2012	Maximum charge per delay and distance
		Khandelwal and Singh 2006, Khandelwal and Singh 2009, and Yuan et al. 2014	Maximum charge per delay and distance and some other factors
	Hybrid intelligent methods	Hajihassani et al. 2015, Nguyen et al. 2020, Abbaszadeh Shahri et al. 2021, Qiu et al. 2021, and Fattahi and Hasanipanah 2021	Maximum charge per delay and distance

study and the range of the input and output parameters is listed in Table 2. The full details of these parameters used in the modeling are presented in Table 3.

### Methodology: imperialist competitive algorithm (ICA)

The imperialist competitive algorithm (ICA) is a novel meta-heuristic algorithm based on population that was introduced by Atashpaz-Gargari and Lucas. It copies the socio-political

process of imperialism and imperialistic competition as a source of inspiration. Studies have supported the capability of algorithm to handle different types of optimization problems (Atashpaz-Gargari and Lucas 2007). Like other evolutionary algorithms, ICA begins with a starting solutions population, known as countries, which stands for the concept of the nations. By examining the quality of objective function in each solution, the best countries in the population are selected as imperialists, and the rest are selected as “colonies.” An empire is the set of one imperialist and its colonies (Shokrollahpour et al. 2011). In time, imperialists

**Table 2** Maximum and minimum of input and output parameters used in models

S. No	Parameter	Index	Range
1	Hole diameter (mm)	HDi	150–311
2	Hole depth (m)	HDe	6–43
3	Burden (m)	B	3–10.5
4	Spacing (m)	S	4–13
5	Charge length (m)	ChL	4–38
6	Average explosive per hole (kg)	EPH	75–3526
7	Distance of monitoring point from blasting face (m)	D	85–8500
8	Blastability Index	BI	5.6–14.8
9	Young’s modulus (GPa)	YM	3.2–12.15
10	Poisson’s ratio	PR	0.16–0.38
11	P wave velocity (km/s)	P	1659–4837
12	Velocity of detonation of explosive (km/s)	VOD	3.14–5.8
13	Density of explosive (t/m3)	DOE	0.95–1.4
14	Peak particle velocity (mm/s)	PPV	0.73–98.34

**Table 3** Detail of input and output parameters used in the prediction models

	HDi	HDe	B	S	ChL	EPH	D	BI	YM	PR	P	VOD	DOE	PPV (mm/s)
15	4.8	3	4	1.3	175	0.5	6.6	7.54	0.23	2.7	3.54	1.15	0.95	
16.5	15	6	7.5	8	150	0.2	10.3	3.88	0.22	2.55	4.36	1.1	4.47	
16.5	12.5	5	7	7.4	512	0.35	10.2	6.81	0.34	1.85	3.67	1.15	4.62	
16.5	7	3	4	4	93	0.25	8.75	6.81	0.24	3.42	5.04	1.05	15.45	
16.5	8.5	3.8	3.8	5.3	375	0.55	7.3	7.54	0.18	2.74	4.17	1.2	1.38	
25	35	7	7	28	2025	5	6.2	6.46	0.28	3.25	4.98	1.2	1.64	
25	39	9	9	32.75	2300	0.6	9.75	7.38	0.22	4.2	4.72	1.2	43.8	
25	39	9	9	32.75	2300	0.4	8.1	6.44	0.35	2.26	4.12	1.3	62.4	
26.9	34.5	9	9	28.5	2300	2.8	8.5	4.15	0.27	2.74	4.8	1.3	6.38	
26.9	39	9	9	32.75	2300	0.35	8.7	5.51	0.2	2.87	3.83	1.2	69.8	
26.9	39	9	9	32.75	2300	0.45	7.68	6.2	0.28	3.12	3.38	1.25	55.4	
26.9	39	9	9	32.75	2300	0.55	8.75	8.11	0.25	3.65	4.37	1.1	47.5	
26.9	39	9	9	32.75	2300	0.5	8.75	9.67	0.21	3.37	3.96	1.15	52.9	
31.1	43	10.5	10.5	37.5	3420	0.4	11.6	6.81	0.34	3.81	5.1	1.15	71.3	
31.1	43	10.5	10.5	37.5	3377	1.2	8.4	7.54	0.27	3.27	4.88	1.3	36.8	
31.1	39	9	9	33	2441	1.8	9.1	8.11	0.21	2.28	3.79	1.2	9.37	
31.1	43	10.5	10.5	37.5	3420	1.08	8.23	5.19	0.3	1.89	5.23	1.3	27.4	
31.1	43	10.5	10.5	37.5	3370	0.35	8.31	7.54	0.26	2.45	3.92	1.2	92.3	
31.1	40.5	9	9	33.5	2535	2.1	7.56	7.54	0.23	3.05	4.24	1.2	6.37	
31.1	32	9	9	24.5	2000	1.79	12.9	5.26	0.26	2.08	4.83	1.2	6.4	

make attempt to widen their characteristics to their colonies, while what we deal with is not a perfectly controlled procedure and the risk of revolution is always present. Countries may leave an empire for another when there is a higher chance for promotion for them. The ICA is widely used to solve different types of optimization problems. For instance the method has been utilized for stock market forecasting (Sadaei et al. 2016), digital filter design (Sharifi and Mojallali 2015), traveling salesman problems (Ardalan et al. 2015), multi-objective optimization (Maroufmashat et al. 2014), integrated product mix-outsourcing problem (Nazari-Shirkouhi et al. 2010), production planning of open pit mines (Mokhtarian Asl and Sattarvand 2016), and scheduling problem (Behnamian and Zandieh 2011; Lian et al. 2012).

Figure 1 shows the flowchart of imperialist competitive algorithm. In the following, the methodology of implementation of ICA is described step by step:

Step 1: generating initial empires. Before starting the optimization algorithm, we need a starting population of  $N_{pop}$  solutions where  $N_{imp}$  of the most powerful are chosen as imperialists. The remaining population ( $N_{col} = N_{pop} - N_{imp}$ ) act as the colonies of the pertinent empires. To create primary empires, colonies are allocated randomly to the imperialists based on their power, so that empires with higher power gain more colonies. To make colonies distribution proportional, normalized cost of  $n^{th}$  imperialist is defined as follows (Nazari-Shirkouhi et al. 2010):

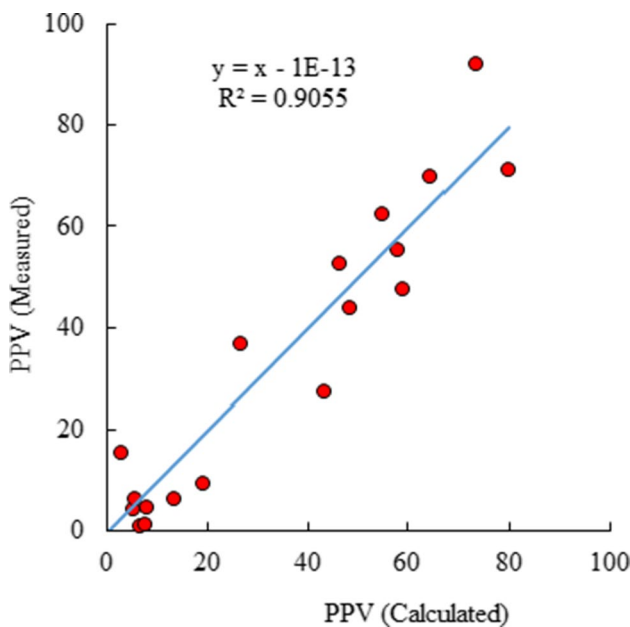


Fig. 1 Correlation of measured and estimated PPV for the linear model

$$C_n = \max\{c_i\} - c_n, i = 1, 2, \dots, N_{imp} \tag{1}$$

where  $c_n$  and  $C_n$  stand for the cost and the normalized cost of  $n^{th}$  imperialist, respectively. Hence, the normalized power of each imperialist can be determined as (Nazari-Shirkouhi et al. 2010)

$$pow_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{2}$$

The number of colonies that each imperialist controls is determined by the normalized power. Therefore, the starting count of colonies of an empire is obtained as (Nazari-Shirkouhi et al. 2010)

$$ColEmp_n = round(pow_n \times N_{col}) \tag{3}$$

where  $ColEmp_n$  stands for the initial number of the colonies of the  $n^{th}$  empire that are chosen randomly from the whole colony population.

Step 2: assimilation process. The colony moves towards the imperialist based on a variety of socio-political axes like culture and language. That is, the colony steps toward the imperialist by  $x$  units wherein  $x$  stands for a random number with uniform distribution.

Step 3: revolution. Revolution operator adds new features to ICA to examine more new regions. Revolution mechanism stops the algorithm from being trapped in local optima (Mortazavi et al. 2015). For this purpose, the weakest colony in each repetition is found, and a new one replaces it randomly.

Step 4: replacing the imperialist with a colony. It is possible for a colony to reduce its cost below that of the imperialist. If so, the imperialist and colony exchange their places.

Step 5: calculating total power of an empire. To calculate the total power of an empire, we need to know the power of its imperialist country; still, the powers of its individual colonies are also effective, although relatively insignificant. Therefore, the total cost of an empire is (Atashpaz-Gargari and Lucas 2007)

$$TC = cost(imperialist_n) + \xi mean(cost(empire_n colonies)) \tag{4}$$

where  $TC$  stands for the total cost of the  $n^{th}$  empire and  $\xi$  stands for a positive number less than 1.

Step 6: imperialistic competition. The competition is modeled by choosing the weakest colony of the weakest empire and making the empires to fight for this colony. The probability of possessing each empire is proportional to its total power. The normalized total cost of

each empire is determined as (Atashpaz-Gargari and Lucas 2007)

$$NTC_n = \max\{TC_i\} - TC_n, i = 1, 2, \dots, N_{imp} \tag{5}$$

where  $TC_n$  and  $NTC_n$  stand for total cost and normalized total cost of  $n$ th empire, respectively. Now the probability of possession of each empire is as follows (Atashpaz-Gargari and Lucas 2007)

$$P_n = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \tag{6}$$

To distribute the colonies among empires based on their possession probability, vector  $P$  is developed as follows (Atashpaz-Gargari and Lucas 2007):

$$P = [p_1, p_2, p_3, \dots, p_{N_{imp}}] \tag{7}$$

Then, the vector  $R$  that is equal to  $P$  in size and of which the elements are uniformly distributed random numbers at [0 1] interval is formed:

$$P = [r_1, r_2, r_3, \dots, r_{imp}], r_1, r_2, r_3, \dots, r_{imp} \sim U(0, 1) \tag{8}$$

Thus, vector  $D$  is obtained by subtracting  $R$  from  $P$ :

$$D = P - R = [d_1, d_2, d_3, \dots, d_{N_{imp}}] = [p_1 - r_1, p_2 - r_2, p_3 - r_3, \dots, p_{N_{imp}} - r_{N_{imp}}] \tag{9}$$

Based on vector  $D$ , the colonies in an empire for the related index in  $D$  is highest win the possession competition (Atashpaz-Gargari and Lucas 2007):

Step 7: deleting the powerless empires. Empires without power will collapse throughout the imperialistic competi-

tion, and other empires possess their colonies. Here, an empire collapses by losing all its colonies (Atashpaz-Gargari and Lucas 2007).

Step 8: stopping criteria. The algorithm keeps going, while there is an iteration remained or an empire remains in the world.

### Estimation of PPV

#### PPV estimation by using multivariate linear regression model

The objective of multivariate regression analysis is to find the values of parameters of a function to make it best fit a set of data. In the case of linear regression with more than one independent variable, multivariate linear regression analysis (MVLRA) is the best option to find the best-fit equation. To obtain the constants coefficients, all 20 sets of data are entered in Microsoft Excel program; the relationship is found to be as follows:

$$PPV = 446.2 - 6.32 \times HDi + 2.44 \times HDe + 14.39 \times B - 24.23 \times S - 0.75 \times ChL + 0.05 \times EPH - 10.84 \times D + 3.05 \times BI - 5.54 \times YM + 58.91 \times PR - 3.33 \times P - 16.79 \times VOD - 198.71 \times DOE \tag{10}$$

Regression statistics and ANOVA obtained from the Excel output are presented in Table 4. This model is validated using the analysis of variance (Table 4) at a confidence level of 95%.

Figure 2 shows the estimated vales versus the measured values. A relatively good agreement can be seen between two sets of values. However, in the next section, a non-linear model based on ICA with higher accuracy is used.

**Table 4** Regression statistics and ANOVA obtained from the Excel output

Regression statistics					
Multiple R	0.951582624				
R Square	0.905509489				
Adjusted R square	0.80078005				
Standard error	15.87369824				
Observations	20				
ANOVA					
	df	SS	MS	F	Significance F
Regression	13	14,488.12888	1114.471452	4.422956908	0.039080063
Residual	6	1511.845775	251.9742958		
Total	19	15,999.97466			

### PPV estimation by using multivariate non-linear regression model based on ICA

This study tries to develop PPV estimation models using ICA optimization technique. The new non-linear estimator model is proposed. ICA has used to determine the non-linear model coefficients. A method that is appropriate for this procedure is called the non-linear least squares fitting. This process minimizes the value of the mean squared error (MSE) of the difference between estimated and measured values. The mean square error (MSE) is

selected as the objective function, and its purpose is to lower the function to its minimum value. The objective function (MSE) is as follows:

$$Minimize \frac{1}{n} \sum_{i=1}^n (PPV_{Est} - PPV_{Measu})^2 \tag{11}$$

$PPV_{Measu}$  is the observed and measured PPV,  $PPV_{Est}$  is the estimated PPV by using model, and  $n$  is the number of observations. In fact, in the ICA model, the fitness function is the total error given by Eq. (11), which should be minimized, and so it can be written in extended form with following notations as follows:

$$Minimize \sum_{i=1}^n \left( \left| \begin{matrix} k_0 + k_1 \times HD_i^{k_2} \times HDe_i^{k_3} \times B_i^{k_4} \times S_i^{k_5} \\ \times ChL_i^{k_6} \times EPH_i^{k_7} \times D_i^{k_8} \times BI_i^{k_9} \times YM_i^{k_{10}} \\ \times PR_i^{k_{11}} \times P_i^{k_{12}} \times VOD_i^{k_{13}} \times DOE_i^{k_{14}} \end{matrix} \right| - PPV_i \right)^2 \tag{12}$$

Different variables related to Eq. (12) have been introduced in previous sections. The estimated  $PPV$ ,  $PPV_{Est}$  values are

$$PPV_{Est} = k_0 + k_1 \times HD_i^{k_2} \times HDe_i^{k_3} \times B_i^{k_4} \times S_i^{k_5} \times ChL_i^{k_6} \times EPH_i^{k_7} \times D_i^{k_8} \times BI_i^{k_9} \times YM_i^{k_{10}} \times PR_i^{k_{11}} \times P_i^{k_{12}} \times VOD_i^{k_{13}} \times DOE_i^{k_{14}} \tag{13}$$

In order to use the ACI optimization method, in this work, the C++ program is generalized for estimating PPV. After optimizing with the ICA, the optimized values are achieved for the constants of non-linear regression. As a result of analysis, the best equation obtained from ACI-based is formulated in Eq. (14).

$$PPV_{Est_{ICA}} = \left| \begin{matrix} 1.494 \\ -0.116 \times HD_i^{1.363} \times HDe_i^{-3.299} \times B_i^{-3.85} \times S_i^{2.547} \\ \times ChL_i^{4.59} \times EPH_i^{-0.1462} \times D_i^{-1.252} \times BI_i^{-1.291} \times YM_i^{0.325} \\ \times PR_i^{-0.224} \times P_i^{0.497} \times VOD_i^{1.208} \times DOE_i^{2.236} \end{matrix} \right| \tag{14}$$

A comparison of measured and estimated outputs from the ICA-based model is presented in Fig. 3. The diagonal line in the figure stands for the perfect goodness of fit. The result illustrates that the estimated inflections are coincident to the measured ones. The coefficient of correlation is found to be high for the proposed ACI-based estimator. This gives better estimation of PPV as compared to the linear model for the case study.

### Results and discussion

The performance of different estimator models can be controlled by correlation coefficient (R), root mean square error (RMSE), variance absolute relative error (VARE), median absolute error (MEDAE), mean absolute error (MAE), and

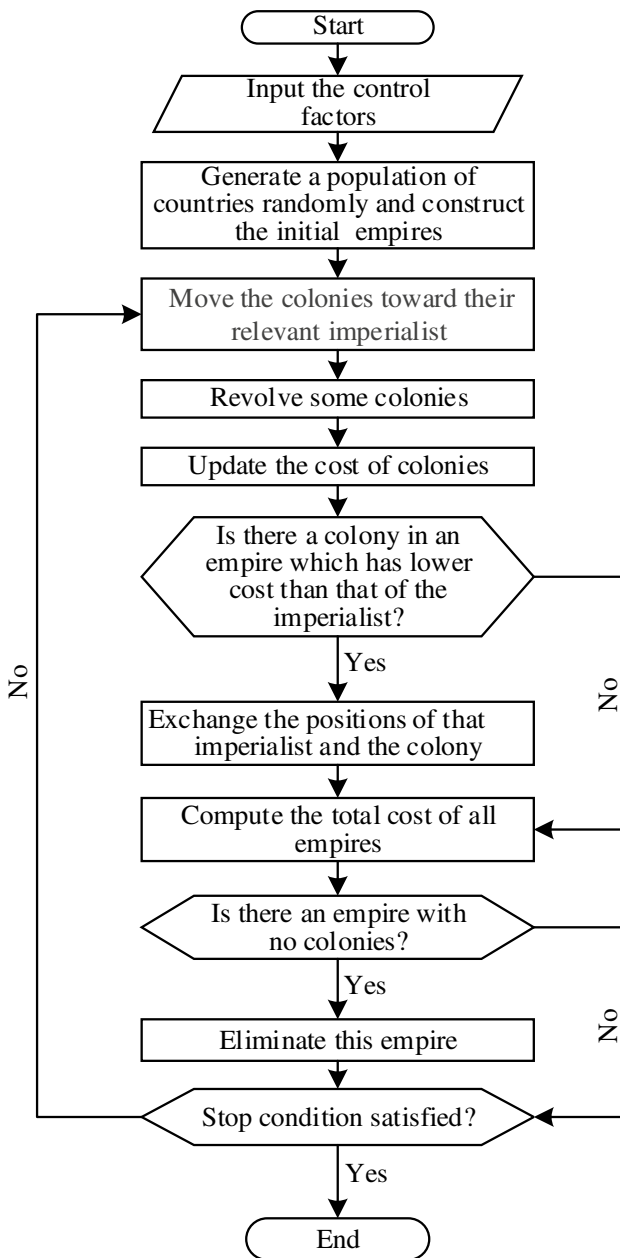
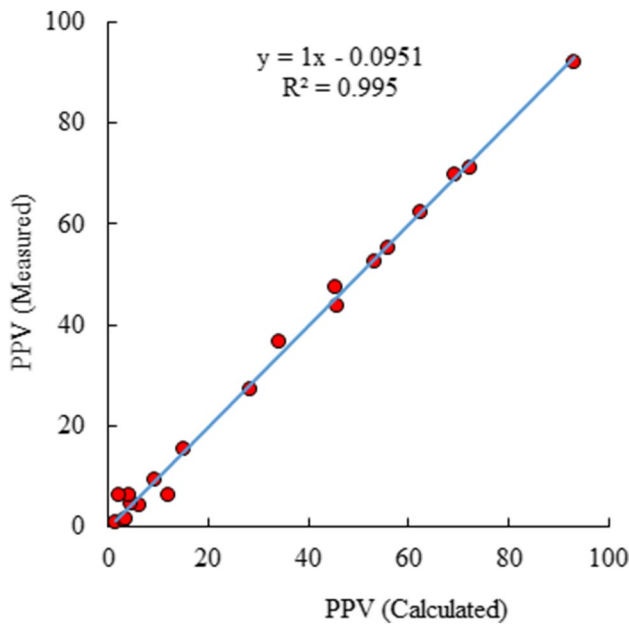


Fig. 2 Flowchart of imperialist competitive algorithm





**Fig. 3** Correlation of measured and estimated PPV for the ACI model

variance absolute error (VARAE). The formulation of these indices can be found in Table 5.

ACI-based model with higher correlation coefficient as well as lower RMSE, VARE, MEDAE, MAE, and VARAE show better performance. The results of assessment according to the mentioned regressions goodness statistical criteria are presented in Table 6.

### Conclusions

A number of researchers studied the blast-induced vibrations to formulate PPV. PPV is a key factor in blast pattern designing. Since rock mass parameters, characteristics of explosive, and blast design parameters vary from one case to another, it is necessary to determine a specific model for each case study in order to decrease the PPV. Considering all the effective factors in a simple model is difficult. In this study, an ICA-based non-linear multivariate model was established to estimate PPV. The model estimated PPV value as output parameters for a given burden, spacing, charge length, hole diameter, hole depth, explosive per hole, distance from blast face, rock mass blastability, Poisson ratio, Young’s modulus, P wave velocity, VOD, and explosive density.

The research finding showed that model values were close to the desirable real ones. The determination coefficient between estimated and measured PPV values ( $R^2$ ) in the ICA-based model was equal to 0.995 and 0.905 for the linear regression model. Also, as shown by the comparison, adding the statistical tests values of the proposed non-linear ICA-based model outperformed the linear model in terms of estimation accuracy.

The ICA-based equation showed very capable values of goodness tests such as RMSE, VARE, MEDAE, MAE, and VARAE which presented acceptable relation between the PPV and effective factors; thus, the proposed non-linear model is recommended for estimating the ground vibration due to blasting in the case study.

**Table 5** Statistical criteria for controlling the performance of the estimator models

Statistical criteria	Formulation
Correlation coefficient, $R$	$CC = \frac{\sum_{i=1}^{i=n} [(PPV_{Meas}^i - \overline{PPV}_{Meas}^i)(PPV_{Esti}^i - \overline{PPV}_{Esti}^i)]}{\sqrt{\sum_{i=1}^{i=n} (PPV_{Meas}^i - \overline{PPV}_{Meas}^i)^2 \times \sum_{i=1}^{i=n} (PPV_{Esti}^i - \overline{PPV}_{Esti}^i)^2}}$
Root mean square error, $RMSE$	$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^{i=n} (PPV_{Meas} - PPV_{Esti})^2}$
Variance absolute relative error, $VARE$	$VARE = \text{var}\left(\left \frac{PPV_{Meas} - PPV_{Esti}}{PPV_{Meas}}\right \right) \times 100$
Median absolute error, $MEDAE$	$MEDAE = \text{median}\left(\left \frac{PPV_{Meas} - PPV_{Esti}}{PPV_{Meas}}\right \right)$
Mean absolute error, $MAE$	$MAE = \frac{1}{n} \times \sum_{i=1}^{i=n}  PPV_{Meas}^i - PPV_{Esti}^i $
Variance absolute error, $VARAE$	$VARAE = \text{var}\left( PPV_{Meas} - PPV_{Esti} \right) \times 100$

**Table 6** Results of regression goodness statistical criteria

Model	RMSE	VARE	MEDAE	MAE	VARAE	CC
Multivariate linear model	8.69	234.75	0.25	7.39	20.86	0.957
ICA-based multivariate non-linear model	1.99	14.41	0.043	1.46	1.87	0.998

## Declarations

**Conflict of interest** The authors declare no competing interests.

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