

# Feasibility of ICA in approximating ground vibration resulting from mine blasting

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**Abstract** Precise prediction of blast-induced ground vibration is an essential task to reduce the environmental effects in the surface mines, civil and tunneling works. This research investigates the potential of imperialist competitive algorithm (ICA) in approximating ground vibration as a result of blasting at three quarry sites, namely Ulu Tiram, Pengerang and Masai in Malaysia. In ICA modeling, two forms of equations, namely power and quadratic, were developed. For comparison aims, several empirical models were also used. In order to develop the ICA and empirical models, maximum charge weight used per delay ( $W$ ) and the distance between blasting sites and monitoring stations ( $D$ ) were utilized as the independent variables, while, peak particle velocity (PPV), as a blast-induced ground vibration descriptor, was utilized as the dependent variable. Totally, 73 blasting events were monitored, and the values of  $W$ ,  $D$  and PPV were carefully measured. Two statistical functions, i.e., root mean square error and coefficient of

multiple determination ( $R^2$ ) were used to compare the performance capability of those prediction models. Simulation results show that the proposed ICA quadratic form can get more accurate predicting results than the ICA power form and empirical models.

**Keywords** Blasting · Peak particle velocity · Imperialist competitive algorithm · Empirical models

## 1 Introduction

Rock excavation is one of the most important steps in surface mines, tunneling and civil works. In this regard, blasting operation is an economical and a common and a widely utilized method. Nevertheless, a huge amount of blasting energy is wasted to produce several undesirable phenomena, such as ground vibration, flyrock, back break and air overpressure [1–11]. Among the mentioned environmental issues, ground vibration is considered as the most unwanted effect produced by blasting which can cause severe damage to the surrounding structures. Therefore, accurately approximating the blast-induced ground vibration is very significant. The several descriptors, including peak particle velocity (PPV), displacement, acceleration and frequency can be applied to evaluate the level of ground vibration. Among them, PPV is the most well-known descriptor for vibration measurement and is widely used in many studies [12–20]. The effective parameters on the PPV may be divided into two main groups including blast design parameters and related parameters to rock mass properties [21–28]. Blast design parameters or controllable parameters such as stemming, spacing, burden, sub-drilling, maximum charge weight used per delay ( $W$ ), blast-hole diameter, blast-hole depth

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and specific charge can be changed by the explosive engineers. Whereas, the related parameters to rock mass properties or uncontrollable parameters, such as compressive and tensile strength, cannot be changed by the explosive engineers. Based on the literature [29–31],  $W$  and distance between blasting site and monitoring stations ( $D$ ) are the most influential parameters on the blast-produced PPV. A number of researchers and institutes have been proposed different empirical models for the prediction of blast-induced PPV [32–41]. According to some studies (e.g., [28, 30]), the performance estimation of the empirical models are not good enough, while the suitable prediction of PPV is necessary. As an example, several empirical models were used for the estimation of PPV in the study conducted by Hasanipanah et al. [42]. Their results indicate that the accuracy of the empirical models is not good enough. Recently, application of such models like artificial intelligent (AI) in approximating problems in science and engineering areas, especially in the field of mining and civil [43–50], has been highlighted by various scholars. For predicting PPV, many researchers used AI techniques as their main methodology. Monjezi et al. [30] employed several empirical models and artificial neural network (ANN) for the prediction of blast-produced PPV at Shur river dam, in Iran. As a result, it was found that the ANN indicates a better prediction capability than empirical models. Support vector machine (SVM) and empirical models were proposed for the prediction of PPV in the study conducted by Khandelwal [51]. He used 150 datasets which were collected from Sinagreni Collieries Company Limited (SCCL), India. He concluded the SVM has superior fitting specification for PPV prediction compared to the used empirical models. A comprehensive study for the prediction of blast-produced PPV by fuzzy logic (FL) and empirical models were presented by Ghasemi et al. [28]. Their datasets were obtained from Sarcheshmeh copper mine, in Iran. They demonstrated that FL provided more accurate predictions in comparison with empirical models. In the other study of the AI methods, Armaghani et al. [52] investigated the results of blast-produced PPV at ISB granite quarry, in Malaysia. They developed ANN, empirical models and adaptive neuro-fuzzy inference system (ANFIS) for approximating PPV. Finally, it was revealed that ANFIS can estimate PPV better than ANN and empirical models. Recently, Amiri et al. [31] proposed a hybrid model of ANN and  $K$ -nearest neighbors (KNN) for forecasting of the PPV. In their studies, ANN and the United States Bureau of Mines (USBM) models were also applied. They showed that ANN-KNN model is more suitable for forecasting of the PPV compared to the ANN and USBM models. In this study, imperialist competitive algorithm (ICA) is proposed to get a precise and

reliable equation for the predicting the PPV in three quarry sites, namely Ulu Tiram, Pengerang and Masai, Malaysia. For comparison purposes, the most well-known empirical models were also developed. The rest of the present research is organized as follows. Detail of the studied cases is given in Sect. 2. In Sect. 3, the ICA is shortly described. Then, developments of empirical techniques as well as ICA in estimating PPV will be discussed in Sects. 4 and 5, respectively. Evaluation of the developed models (Sect. 6) will be given before conclusions of the study (Sect. 7).

## 2 Field investigation

In this section, the studied cases and collection of datasets are shortly explained. Three granite quarry sites, i.e., Ulu Tiram, Pengerang and Masai near, in Malaysia, were considered in the present research work (see Fig. 1). The Ulu Tiram, Pengerang and Masai sites are located 18, 62 and 25 km of Johor City, at  $103^{\circ}49'20''E$ ,  $104^{\circ}7'58''E$  and  $103^{\circ}52'27.79''E$  Longitudes as well as at  $1^{\circ}36'41''N$ ,  $1^{\circ}22'58''N$  and  $1.5^{\circ}29'42.16''N$  Latitudes, in order. In these sites, drilling and blasting methods is used in order to fragment the rock mass. In the drilling process, Wagon Drill Machine is mainly used, and the blast-hole diameters are 75, 115 and 150 mm. Also, in the blasting process, ANFO was utilized as the main explosive material. Moreover, fine gravels are used to stem the blast-holes and the benches height in the The Ulu Tiram, Pengerang and Masai sites are 10–15, 10–30 and 5–30 m, respectively. Ground vibration is the most undesirable phenomena produced by blasting operations in the mentioned sites. Therefore, accurate prediction of blast-produced ground vibration is very significant. For this aim, 73 blasting events were monitored, and the values of  $W$ ,  $D$  and PPV in kg, m and mm/s, respectively, were measured. In the other words,  $W$  and  $D$  were considered as independent parameters, and PPV was considered as dependent or target parameter. Table 1 and Figs. 2, 3 and 4 show the range and the frequency distributions of the  $W$ ,  $D$  and PPV in this research, respectively.

## 3 Imperialist competitive algorithm

The imperialism competitive algorithm (ICA) which was developed by Atashpaz-Gargari and Lucas [53] is considered as one of the global search population-based algorithms to optimize science and engineering problems. Similar to some other optimization algorithms like genetic algorithm (GA) and particle swarm optimization (PSO), ICA starts with a random initial population called



Fig. 1 Studied cases in this research

Table 1 Used parameters and their range

Parameter	Symbol	Unit	Min	Max
Maximum charge weight used per delay	$W$	kg	148	367
Distance between blasting sites and monitoring station	$D$	m	85	298
Peak particle velocity	PPV	mm/s	0.08	6.40

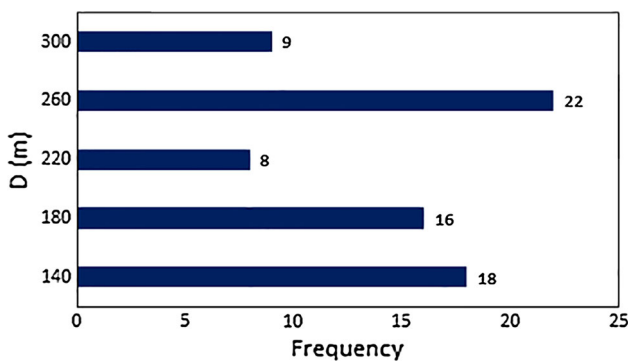


Fig. 2 Frequency histogram of the measured  $D$

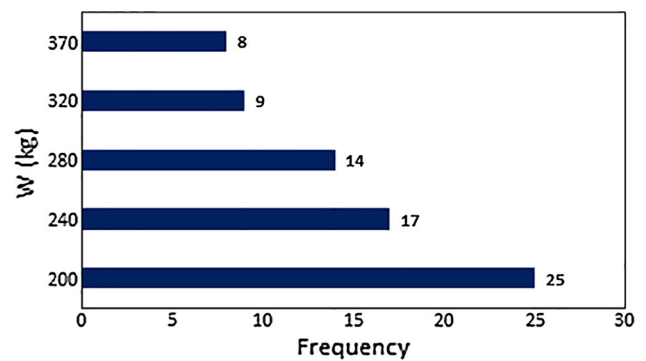


Fig. 3 Frequency histogram of the measured  $W$

countries. After creating  $N$  countries (also named as  $N_{country}$ ), some of them with the lowest costs or objective functions, for instance, root mean square error (RMSE), are chosen as the imperialists ( $N_{imp}$ ). Therefore, colonies or  $N_{col}$  are defined as the remaining countries. All colonies are

distributed among the empires in accordance with the initial power of them. So, it is clear that the more powerful imperialists (lowest RMSE) can attract more colonies. In ICA, there are three algorithm operators, i.e., assimilation, revolution and competition [53]. Colonies attract to the

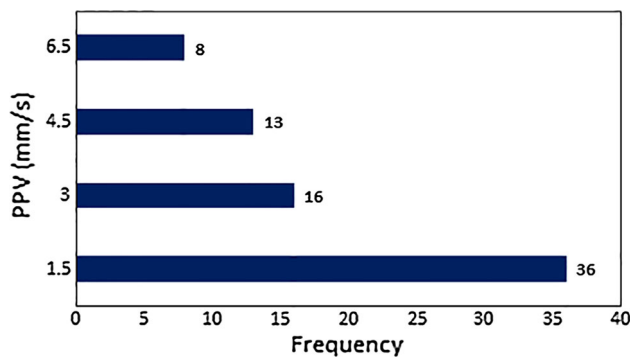


Fig. 4 Frequency histogram of the measured PPV

imperialists through assimilation operator. With the help of revolution operators, some sudden changes in the locations of the countries will happen. Through these two operators, for a colony, there is a possibility to reach a state better than its imperialist state.

In the last ICA operator or competition, imperialists try to adopt more number of colonies. During competition, there is a competition among all empires to obtain the colonies of other empires. All of the empires have at least a chance to adopt one colony of the weakest empire based on their power. After a few decades, the weak empires will be gradually collapsed, and on the other hand, more powerful empires increase their power. The mentioned procedures will be continued until all of the empires (except the most powerful ones) collapse or a termination criterion is met. Here, termination criteria can be defined as root mean square error (RMSE) or maximum number of decade. It should be noted that in ICA, the maximum number of decades ( $N_{decade}$ ) works like the number of iteration ( $N_{ite}$ ) in PSO algorithm. Figure 5 illustrates a flowchart of ICA algorithm. Nevertheless, the focus of this paper is not to cover ICA mathematical formulation. More details in this regard can be found in the previous studies (e.g., [7, 54, 55]).

#### 4 Prediction of PPV by empirical models

In the present paper, the most conventional empirical models are utilized for forecasting of the blast-produced PPV, as listed in Table 2. In this Table, PPV,  $W$  and  $D$  are in terms of mm/s, kg and m, respectively. Also,  $K$ ,  $n$ ,  $a$ ,  $b$  are site constants and can be determined from the multiple regression analysis.

The total datasets were considered, and then, the site constants were calculated using SPSS version 16 (SPSS 2007). Table 3 summarizes the values of site constants for the used empirical models in this paper. The performance of the empirical models is evaluated in Sect. 6.

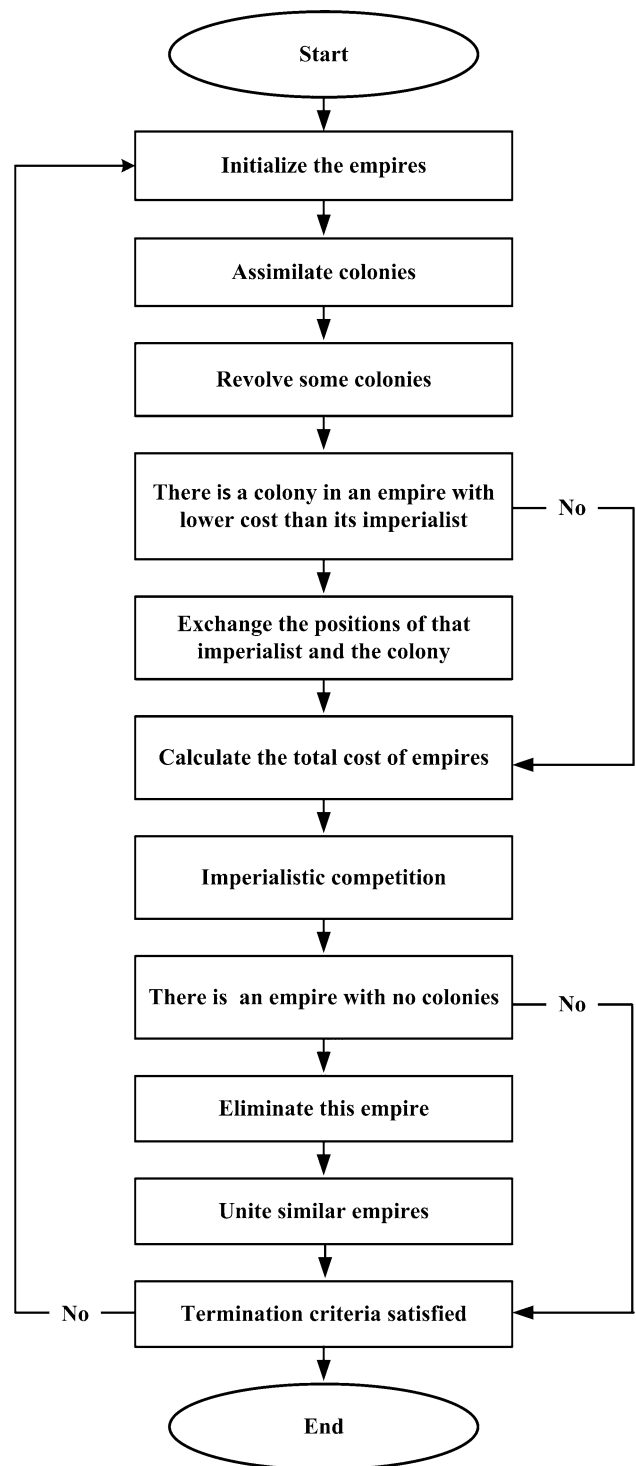


Fig. 5 ICA algorithm

#### 5 Prediction of PPV by ICA

The present section describes model development procedure of ICA in estimating PPV, considering two model inputs, i.e.,  $D$  and  $W$ . In this regard, two ICA models, i.e., power and quadratic are proposed for forecasting of the



**Table 2** Used empirical models in this research

Empirical models	Equation
USBM [32]	$PPV = k \times \left[ \frac{D}{\sqrt{W}} \right]^n$
Langefors-Kihlstrom [33]	$PPV = k \times \left[ \sqrt{\frac{W}{D^3}} \right]^n$
Roy [40]	$PPV = n + \left[ k \times \left[ \frac{D}{\sqrt{W}} \right]^{-1} \right]$
Rai-Singh [41]	$PPV = k \times D^a \times W^b \times e^{(c \times D)}$

**Table 3** Calculated values of site constants

Empirical equation	Site constants				
	<i>k</i>	<i>n</i>	<i>a</i>	<i>b</i>	<i>c</i>
USBM	63.72	-1.44	-	-	-
Langefors-Kihlstrom	15.05	1.81	-	-	-
Roy	36.94	-1.26	-	-	-
Rai-Singh	0.16	-	-0.31	0.97	-0.006

blast-produced PPV. As the first stage, in order to develop a model with lower errors, it is well established to normalize the prepared database before modeling. Therefore, all 73 datasets should be normalized considering the following equation which its range is between 0 and 1:

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where  $X_n$  and  $X$  are the normalized and measured values, respectively. Also, the minimum and maximum of measured dataset are  $X_{\min}$  and  $X_{\max}$ , respectively. As mentioned before, two functions of power and quadratic were applied for forecasting of the blast-produced PPV and then using ICA, their coefficients were found. The general forms of power and quadratic functions are presented in Eqs. (2) and (3), respectively:

$$y = ax^b \tag{2}$$

$$y = ax^2 + bx + c \tag{3}$$

where  $a$ ,  $b$  and  $c$  are constants. Note that,  $b$  in power function is any nonzero real number. By this introduction, power function type of the problem of this study can be shown as follows:

$$PPV_P = x_1 + x_2 D^{x_3} + x_4 W^{x_5} \tag{4}$$

In addition, quadratic function of the PPV problem can be formed based on the following equation:

$$PPV_P = x_1 + x_2 D^2 + x_4 W^2 + x_5 DW \tag{5}$$

In the above equations,  $W$  and  $D$  are set as independent parameter of the system, while PPV is considered as dependent parameter.

Here, the role of ICA in determining the optimal values of coefficients will be highlighted. In fact, based on the lowest values of fitness function, ICA attempts to find the fittest model or models to the available data. Of course, this is possible through minimizing errors between the measured values of PPV and the predicted ones. Hence, the used fitness function for solving problem of this study can be defined as follows:

$$f(x) = \sum_{i=1}^m (PPV_{\text{measured}} - PPV_{\text{predicted}})^2 \tag{6}$$

where  $f(x)$  is defined as the fitness function,  $PPV_{\text{measured}}$  and  $PPV_{\text{predicted}}$  are measured PPVs and predicted ones by the system, respectively. It should be mentioned that the minimum value of the above equation in the solution of this study. An ICA code was written by the authors in MATLAB environmental software, and all modeling stages were conducted using MATLAB version 7.14.0.739 [56]. In order to achieve the aim of this study, the optimum ICA parameters should be designed and subsequently utilized. To do this, some of the previous investigations have been reviewed to identify the range of ICA parameters.

According to the original study of ICA [53], parameters like  $\beta$ ,  $\theta$ ,  $\zeta$ , number of country ( $N_{\text{country}}$ ), number of decade ( $N_{\text{decade}}$ ) and number of imperialism ( $N_{\text{imp}}$ ) are the most effective ones on ICA performance. Review of the literature (e.g., [53, 57, 58]) showed that the best values of  $\beta$ ,  $\theta$  and  $\zeta$  are considered as 2,  $\pi/4$  and 0.02, respectively. Therefore, the mentioned values were used in constructing all ICA models. In case of  $N_{\text{country}}$ , many values such as 40, 56, 135 and 250 were recommended in the studies carried out by Ahmadi et al. [57], Marto et al. [59], Hajihassani et al. [55] and Armaghani et al. [60], respectively, for solving engineering problems.  $N_{\text{decade}}$  of 800, 500 and 400 were suggested by Armaghani et al. [7, 60, 61], respectively. Moreover, Hajihassani et al. [55], Marto et al. [59] and Armaghani et al. [60] recommended values of 11, 9 and 25, respectively, as  $N_{\text{imp}}$  for solving geotechnical problems. It seems that there is a need to design these parameters through trial-and-error procedure. Hence, many ICA models were built using different values of  $N_{\text{country}}$ ,  $N_{\text{decade}}$  and  $N_{\text{imp}}$ . The optimal values of  $N_{\text{country}}$ ,  $N_{\text{decade}}$  and  $N_{\text{imp}}$  for both power and quadratic ICA models are shown in Table 4. As presented in this Table, there is no much difference between the obtained ICA results of power and quadratic functions. Considering the obtained ICA parameters in this study, the proposed power and quadratic equations for approximating PPV values resulting from

**Table 4** Obtained values of the ICA parameters

Parameter	Value	
	Power form	Quadratic form
$N_{\text{country}}$	250	300
$N_{\text{decade}}$	300	400
$N_{\text{imp}}$	20	25

**Table 5** Statistical functions results for the predictive models

Model	Statistical functions	
	$R^2$	RMSE
USBM	0.875	0.56
Langefors-Kihlstrom	0.879	0.55
Roy	0.894	0.51
Rai-Singh	0.897	0.5
ICA power form	0.93	0.41
ICA quadratic form	0.94	0.37

blasting operations in Ulu Tiram, Pengerang and Masai sites are shown in Eqs. (7) and (8), respectively.

$$PPV_p = 0.0049D^{-6.35} + 0.00075W^{1.56} - 1.74 \quad (7)$$

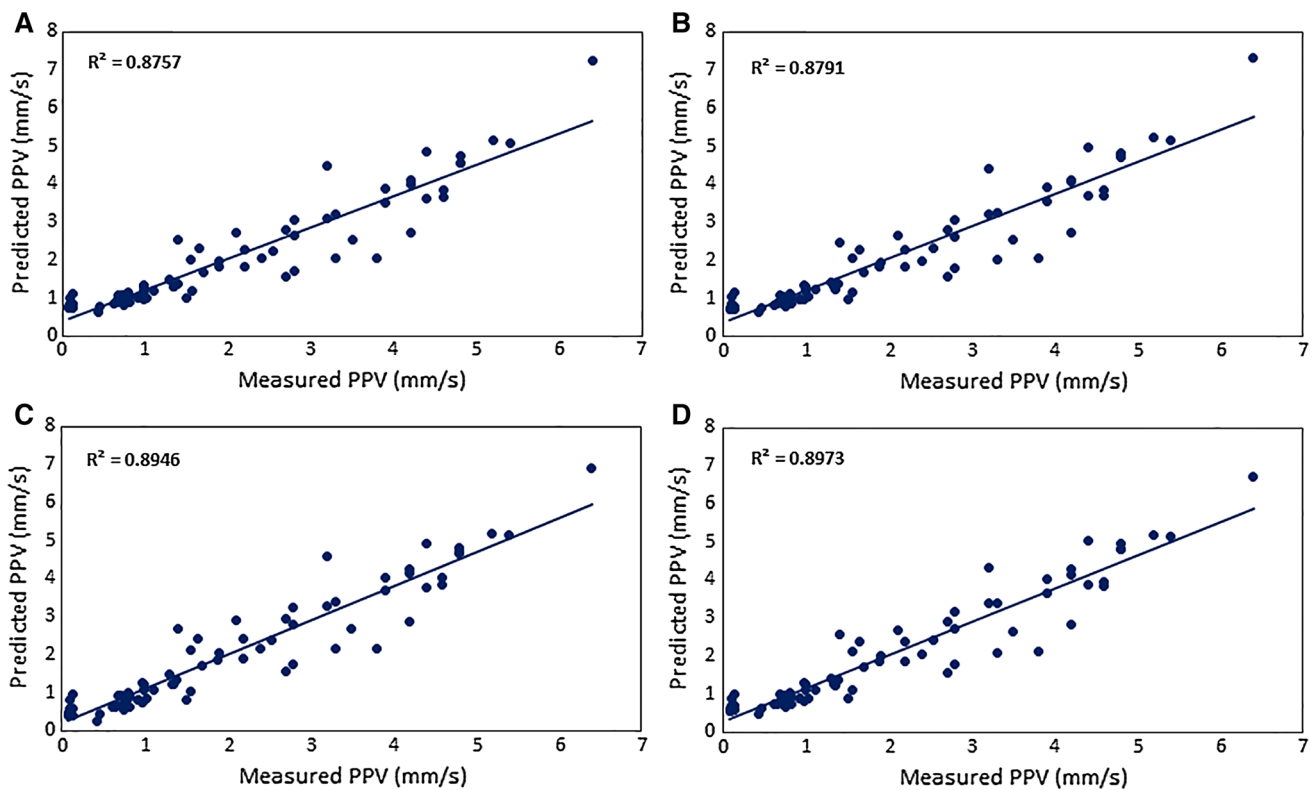
$$PPV_p = 2.68 - (8.2 \times 10^{-6} \times D^2) + (4.14 \times 10^{-5} \times W^2) + (6.3 \times 10^{-5}DW) \quad (8)$$

It is worth noting that the obtained coefficients in Eqs. (7) and (8) were computed using the actual datasets, not the normalized ones. More details regarding the performance of the proposed ICA power and ICA quadratic equations for the prediction of PPV will be given in Sect. 6.

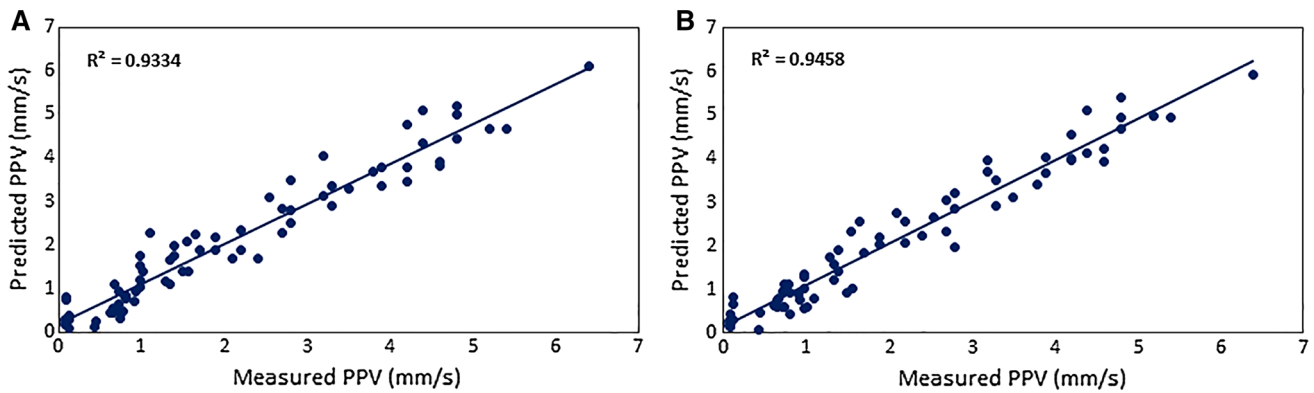
### 6 Analysis and results

In the present study, two ICA models namely power and quadratic as well as several empirical models were presented for predicting of the blast-produced PPV in three site quarries in Malaysia. In this regard, the total datasets (73 data) were considered, and the  $W$  and  $D$  were set as independent parameters, while PPV was set as dependent parameter. The performance of the developed predicting models is carried out using two statistical functions, i.e., root mean square error (RMSE) and coefficient of multiple determination ( $R^2$ ).

$$\text{Root Mean Square Error} = \sqrt{\frac{1}{n} \times \sum_{i=1}^n [(x_i - x_p)^2]} \quad (9)$$



**Fig. 6** Measured versus predicted PPVs by a USBM, b Langefors-Kihlstrom, c Roy, and d Rai-Singh equations



**Fig. 7** Measured versus predicted PPVs by **a** ICA power and **b** ICA quadratic equations

$$R^2 = \frac{\left[ \sum_{i=1}^n (x_i - x_{\text{mean}})^2 \right] - \left[ \sum_{i=1}^n (x_i - x_p)^2 \right]}{\left[ \sum_{i=1}^n (x_i - x_{\text{mean}})^2 \right]} \quad (10)$$

where  $n$  denotes number of datasets and represents the predicted and measured PPV values. For an excellent model, the values of RMSE and  $R^2$  should be close to 0 and 1, respectively. Table 5 summarizes the obtained statistical function values for the predictive models. Furthermore, the relationships between the predicted and measured PPVs are plotted in Figs. 6 and 7. The  $R^2$  were obtained as 0.875, 0.879, 0.894, 0.897, 0.93 and 0.94 for USBM, Langefors-Kihlstrom, Roy, Rai-Singh, ICA power form and ICA quadratic form, respectively. The RMSE was also obtained as 0.56, 0.55, 0.51, 0.5, 0.41 and 0.37 for USBM, Langefors-Kihlstrom, Roy, Rai-Singh, ICA power form and ICA quadratic form, respectively. As a result, the ICA quadratic form possessed superior predictive ability than the ICA power form and empirical models.

## 7 Conclusions

Ground vibration is the most important environmental effect caused by blasting in Ulu Tiram, Pengerang and Masai quarry sites in Malaysia. Hence, accurate prediction of blast-produced ground vibration is critical in these sites. This research explores the possibility of using the ICA to create a model for predicting the PPV. In this regard, two equations namely power and quadratic optimized by ICA were proposed. For comparison aims, several empirical models, i.e., USBM, Langefors-Kihlstrom, Roy and Rai-Singh were also utilized. In order to achieve the aim of this study, 73 blasting events were considered and the most effective parameters on the PPV were measured. For modeling,  $W$  and  $D$  were used as the independent variables, while PPV was used as the dependent variables. The RMSE and  $R^2$  were used for evaluating the accuracy and performance of the models. Finally, the results indicated

the superiority of quadratic form over the other predictive models in the current study. The  $R^2$  were 0.875, 0.879, 0.894, 0.897, 0.933 and 0.945 for the USBM, Langefors-Kihlstrom, Roy, Rai-Singh, power and quadratic forms, respectively. As a conclusion, ICA can be introduced as an acceptable and reliable algorithm in forecasting the PPV.

### Compliance with ethical standards

**Conflict of interest** The authors declare no conflict of interest.

## References

- Singh TN, Verma AK (2010) Sensitivity of total charge and maximum charge per delay on ground vibration. *Geomat Nat Hazards Risk* 1(3):259–272
- Khandelwal M, Singh TN (2013) Application of an expert system to predict maximum explosive charge used per delay in surface mining. *Rock Mech Rock Eng* 46(6):1551–1558
- Trivedi R, Singh TN, Raina AK (2014) Prediction of blast induced flyrock in Indian limestone mines using neural networks. *J Rock Mech Geotech Eng* 6:447–454
- Hasanipanah M, Jahed Armaghani D, Khamesi H, Bakhshandeh Amnieh H, Ghoraba S (2015) Several non-linear models in estimating air-overpressure resulting from mine blasting. *Eng Comput*. doi:10.1007/s00366-015-0425-y
- Trivedi R, Singh TN, Gupta N (2015) Prediction of blast-induced flyrock in opencast mines using ANN and ANFIS. *Geotech Geol Eng* 33:875–891
- Hasanipanah M, Shahnazar A, Bakhshandeh Amnieh H, Jahed Armaghani D (2016) Prediction of air-overpressure caused by mine blasting using a new hybrid PSO–SVR model. *Eng Comput*. doi:10.1007/s00366-016-0453-2
- Jahed Armaghani D, Hasanipanah M, Tonnizam Mohamad E (2016) A combination of the ICA-ANN model to predict air-overpressure resulting from blasting. *Eng Comput* 32(1):155–171
- Tonnizam Mohamad E, Jahed Armaghani D, Hasanipanah M, Murlidhar BR, Alel MNA (2016) Estimation of air-overpressure produced by blasting operation through a neuro-genetic technique. *Environ Earth Sci* 75(2):1–15
- Hasanipanah M, Jahed Armaghani D, Bakhshandeh Amnieh H, Zaimi Abd Majid M, Mahmood MDT (2016) Application of PSO to develop a powerful equation for prediction of flyrock due to blasting. *Eng Comput*. doi:10.1007/s00521-016-2434-1

10. Hasanipanah M, Naderi R, Kashir J, Noorani SA, Zeynali Aaq Qaleh A (2016) Prediction of blast-produced ground vibration using particle swarm optimization. *Eng Comput*. doi:10.1007/s00366-016-0462-1
11. Fouladgar N, Hasanipanah M, Bakhshandeh Amnieh H (2016) Application of cuckoo search algorithm to estimate peak particle velocity in mine blasting. *Eng Comput*. doi:10.1007/s00366-016-0463-0
12. Singh TN (2004) Artificial neural network approach for prediction and control of ground vibrations in mines. *Min Technol* 113(4):251–256
13. Singh TN, Singh V (2005) An intelligent approach to predict and control ground vibration in mines. *Geotech Geol Eng* 23(3):249–262
14. Iphar M, Yavuz M, Ak H (2008) Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. *Environ Geol* 56(1):97–107
15. Monjezi M, Ghafurikalajahi M, Bahrami A (2011) Prediction of blast-induced ground vibration using artificial neural networks. *Tunn Undergr Space Technol* 26:46–50
16. Fisne A, Kuzu C, Hudaverdi T (2011) Prediction of environmental impacts of quarry blasting operation using fuzzy logic. *Environ Monit Assess* 174(1–4):461–470
17. Alvarez-Vigil AE, Gonzalez-Nicieza C, Gayarre Lopez F, Alvarez-Fernandez MI (2012) Predicting blasting propagation velocity and vibration frequency using artificial neural network. *Int J Rock Mech Min Sci* 55:108–116
18. Saadat M, Khandelwal M, Monjezi M (2014) An ANN-based approach to predict blast-induced ground vibration of Gol-EGohar iron ore mine, Iran. *J Rock Mech Geotech Eng* 6:67–76
19. Vasovic D, Kostic S, Ravilic M, Trajkovic S (2014) Environmental impact of blasting at Drenovac limestone quarry (Serbia). *Environ Earth Sci* 72:3915–3928
20. Dindarloo SR (2015) Prediction of blast-induced ground vibrations via genetic programming. *Int J Min Sci Technol* 25(6):1011–1015
21. Khandelwal M, Singh TN (2006) Prediction of blast induced vibrations and frequency in opencast mine: a neural network approach. *J Sound Vib* 289:711–725
22. Khandelwal M, Singh TN (2007) Evaluation of blast-induced ground vibration predictors. *Soil Dyn Earthq Eng* 27:116–125
23. Khandelwal M, Singh TN (2009) Prediction of blast-induced ground vibration using artificial neural network. *Int J Rock Mech Min Sci* 46(7):1214–1222
24. Bakhshandeh Amnieh H, Mozdianfard MR, Siamaki A (2010) Predicting of blasting vibrations in Sarcheshmeh copper mine by neural network. *Saf Sci* 48(3):319–325
25. Monjezi M, Ahmadi M, Sheikhan M, Bahrami A, Salimi AR (2010) Predicting blast-induced ground vibration using various types of neural networks. *Soil Dyn Earthq Eng* 30(11):1233–1236
26. Khandelwal M, Kumar DL, Yellishetty M (2011) Application of soft computing to predict blasting-induced ground vibration. *Eng Comput* 27(2):117–125
27. Mohamed MT (2011) Performance of fuzzy logic and artificial neural network in prediction of ground and air vibrations. *Int J Rock Mech Min Sci* 48(5):845–851
28. Ghasemi E, Ataei M, Hashemolhosseini H (2012) Development of a fuzzy model for predicting ground vibration caused by rock blasting in surface mining. *J Vib Contr* 19(5):755–770
29. Verma AK, Singh TN (2013) Comparative study of cognitive systems for ground vibration measurements. *Neural Comput Appl* 22:341–1643
30. Monjezi M, Hasanipanah M, Khandelwal M (2013) Evaluation and prediction of blast-induced ground vibration at Shur River Dam, Iran, by artificial neural network. *Neural Comput Appl* 22:1637–1643
31. Amiri M, Bakhshandeh Amnieh H, Hasanipanah M, Khanli LM (2016) A new combination of artificial neural network and K-nearest neighbors models to predict blast-induced ground vibration and air-overpressure. *Eng Comput*. doi:10.1007/s00366-016-0442-5
32. Duvall WI, Petkof BB (1959) Spherical propagation of explosion generated strain pulses in rock. *US Bur Mines, RI* 5483
33. Langefors U, Kihlstrom B (1963) The modern technique of rock blasting. Wiley, New York
34. Davies B, Farmer IW, Attewell PB (1964) Ground vibrations from shallow sub-surface blasts. *Engineering* 217:553–559
35. Nicholls HR, Johnson CF, Duvall WI (1971) Blasting vibrations and their effects on structures. *US Bur Mines, RI* 656
36. Indian Standard Institute (1973) Criteria for safety and design of structures subjected to underground blast. *ISI Bull No* 6922
37. German Institute of Standards (1986) Vibration of building effects on structures. *DIN 4150, vol 3, pp* 1–5
38. Siskind DE (2000) Vibrations from blasting. ISEE Publication, Cleveland
39. Gupta RN, Pal Roy P, Singh B (1987) On a blast induced blast vibration predictor for efficient blasting. In: *Proceedings of the 22nd international conference on safety in mines research institute, Beijing, China, pp* 1015–1021
40. Pal Roy P (1991) Vibration control in an opencast mine based on improved blast vibration predictors. *Min Sci Tech* 12(2):157–165
41. Rai R, Singh TN (2004) A new predictor for ground vibration prediction and its comparison with other predictors. *Indian J Eng Mater Sci* 11(3):178–184
42. Hasanipanah M, Monjezi M, Shahnazar A, Jahed Armaghanid D, Farazmand A (2015) Feasibility of indirect determination of blast induced ground vibration based on support vector machine. *Measurement* 75:289–297
43. Singh TN, Kanchan R, Verma AK (2004) Prediction of blast induced ground vibration and frequency using an artificial intelligent technique. *Noise Vib Worldw* 35(11):7–15
44. Verma AK, Singh TN (2011) Intelligent systems for ground vibration measurement: a comparative study. *Eng Comput* 27(3):225–233
45. Singh R, Vishal V, Singh TN (2012) Soft computing method for assessment of compressional wave velocity. *Sci Iran* 19(4):1018–1024
46. Singh R, Vishal V, Singh TN, Ranjith PG (2013) A comparative study of generalized regression neural network approach and adaptive neuro-fuzzy inference systems for prediction of unconfined compressive strength of rocks. *Neural Comput Appl* 23(2):499–506
47. Verma AK, Singh TN (2013) A neuro-fuzzy approach for prediction of longitudinal wave velocity. *Neural Comput Appl* 22(7):1685–1693
48. Verma AK, Singh TN, Maheshwar Sachin (2014) Comparative study of intelligent prediction models for pressure wave velocity. *J Geosci Geomat* 2(3):130–138
49. Kainthola A, Singh PK, Verma D, Singh R, Sarkar K, Singh TN (2015) Prediction of strength parameters of himalayan rocks: a statistical and ANFIS approach. *Geotech Geol Eng* 33(5):1255–1278
50. Verma AK, Sirvaiya A (2016) Intelligent prediction of Langmuir isotherms of Gondwana coals in India. *J Pet Explor Prod Technol* 6(1):135–143
51. Khandelwal M (2011) Blast-induced ground vibration prediction using support vector machine. *Eng Comput* 27:193–200
52. Jahed Armaghani D, Momeni E, Khalil Abad SVAN, Khandelwal M (2015) Feasibility of ANFIS model for prediction of ground



- vibrations resulting from quarry blasting. *Environ Earth Sci* 74:2845–2860
53. Atashpaz-Gargari E, Lucas C (2007) Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In: *IEEE congress on evolutionary computation*, pp 4661–4667
54. Atashpaz-Gargari E, Hashemzadeh F, Rajabioun R, Lucas C (2008) Colonial competitive algorithm, a novel approach for PID controller design in MIMO distillation column process. *Int J Intell Comput Cybern* 1:337–355
55. Hajihassani M, Jahed Armaghani D, Marto A, Mohamad ET (2015) Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. *Bull Eng Geol Environ* 74:873–886
56. Demuth H, Beale M, Hagan M (2009) *MATLAB Version 7.14.0.739; Neural Network Toolbox for Use with Matlab. The Mathworks*
57. Ahmadi MA, Ebadi M, Shokrollahi A, Majidi SMJ (2013) Evolving artificial neural network and imperialist competitive algorithm for prediction oil flow rate of the reservoir. *Appl Soft Comput* 13(2):1085–1098
58. Ebrahimi E, Mollazade K, Babaei S (2014) Toward an automatic wheat purity measuring device: a machine vision-based neural networks-assisted imperialist competitive algorithm approach. *Measurement* 55:196–205
59. Marto A, Hajihassani M, Jahed Armaghani D, Tonnizam Mohamad E, Makhtar AM (2014) A novel approach for blast-induced flyrock prediction based on imperialist competitive algorithm and artificial neural network. *Sci World J*, Article ID 643715
60. Jahed Armaghani D, Mohd Amin MF, Yagiz S, Shirani Faradonbeh R, Abdullah RA (2016) Prediction of the uniaxial compressive strength of sandstone using various modeling techniques. *Int J Rock Mech Min Sci* 85:174–186
61. Jahed Armaghani D, Mohamad ET, Momeni E, Monjezi M, Narayanasamy MS (2016) Prediction of the strength and elasticity modulus of granite through an expert artificial neural network. *Arab J Geosci*. doi:[10.1007/s12517-015-2057-3](https://doi.org/10.1007/s12517-015-2057-3)