RESEARCH ARTICLE

Rock Fragmentation Prediction through a New Hybrid Model Based on Imperial Competitive Algorithm and Neural Network

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Abstract: Reliable estimation of rock fragmentation is an important issue in the blasting operations in order to predict quality of the production. Since rock fragmentation is affected by various parameters such as blast pattern and rock mass characteristics, it is very difficult to have an appreciate prediction of it. This paper describes a new hybrid imperialism competitive algorithm (ICA)-artificial neural network (ANN) in order to solve shortcomings of ANN itself for prediction of rock fragmentation. In fact, the influence of ICA on ANN results was studied in this research. By investigating the related studies, the most important parameters of ICA were identified and a series of parametric studies for their determination were conducted. All models were built using 8 inputs and one output which is rock fragmentation. To have a fair comparison and show the capability of the new hybrid model, a pre-developed ANN model was also considered and constructed. Evaluation of the obtained results demonstrated that a higher ability of rock fragmentation prediction is received developing a hybrid ICA-ANN model. Coefficient of determination (R2) values of (0.949 and 0.813) and (0.941 and 0.819) were obtained for training and testing of ICA-ANN and ANN models, respectively which indicated that the proposed ICA-ANN model can be implemented better in improving performance capacity of ANN model in estimating rock fragmentation.

Keywords: Blasting; rock fragmentation; ICA; ANN; hybrid model.

1. Introduction

Blasting is a well-known economical way of breaking rock. A desired fragmentation is essential as it impacts downstream mining operation of loading, hauling and crushing. As per study by Osanloo and Hekmat (2005)[1], loading efficiency of shovel depends upon bucket fill factor, percentage of oversize fraction and operator's skill. Distribution of fragment size affects bucket fill factor. Decrease in oversize fraction improves shovel productivity. Mean fragment size also determines blasted muck pile characteristics (Singh and Cheung, 2017)[2]. Digging requirement of loading equipment depends upon tightness of muck pile. Dump truck capacity is fully utilized when there is well fragmented rock. Energy consumption is reduced in crushing and grinding operation due to micro-fracturing caused during blasting (Workman and Eloranta, 2003)[3]. Prediction of rock fragmentation due to blasting is important for planning and controlling every mining operation.

In situ rock mass block (XB) is broken into smaller fragment size of rock due to sudden expansion of explosives energy into gaseous form during blasting operation (Hasanipanah et al. 2016a)[4]. Desired Run of Mine (ROM) blast fragmentation is that rock fragment size which is easy for loading and transportation of blasted rock. Mean fragment size (X50) is average blast fragment size of total blasted rock muck pile. If XMax is maximum fragment size, X80 which is 80% of maximum size should be equivalent to maximum permissible feed size of crusher.

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Oversize blasted rock may vary from mine to mine based on loading capacity of excavator and primary crusher. Mid sized mines have oversize fragmentation or boulder of 800 to 1000 mm. Fine fragments are below 10 mm. Blasted stock pile photograph is taken with known size object and rock fragment is analyzed through image analysis software. Table 1 shows various empirical equations which have been used for prediction of blast fragmentation.

Reference	Empirical Equation	Remarks
Kuznetsov (1973)[5]	$X_m = A\left(\frac{V_0}{Q_T}\right)^{0.8} {Q_T}^{1/6}$ (1) X_m is mean fragment size in cm, A the rock factor, V_0 is the blast volume = S X B X H, S=Spacing, B=Burden, H= Bench height in 'm' Q_T is the mass of explosive –energy equivalent of TNT Explosive charge equivalent of each blast hole	Rock mass characteristics and explosive strength accounted. The mean size correlated to the characteristic size of the Rosin–Rammler distribution. The uniformity coefficient unknown.
Cunningham (1983)	$X_m = A\,(K^{-0.8}){Q_e}^{1/6}\left(\frac{115}{S_{ANFO}}\right)^{19/30}$ (2) K is powder factor in kg of explosives per cum of blasted rock. $K = \left(\frac{Qe}{V_0}\right)$ Q_e is total explosives charge in Kg S_{ANFO} relative strength of explosive with respect to ANFO	Suitable to calculate mean fragmentation size for a given powder factor. Cunningham (1983)[6] suggested rock factor to be on the basis of rock mass description (massive, jointed or friable), joint spacing, density of rock, UCS and Young's modulus.
Rosin and Rammler (1933)[7]	$R = e^{-(X/X_c)}$ (3) where R is the mass fraction larger than size X, X = diameter of fragment (cm), Xc = the characteristic size (cm), n the Rosin–Rammler exponent or uniformity index, and e the base of natural logarithms, 2.7183. $X_c = \frac{X_m}{(0.693)^{1/n}}$ (4) Equation (3) is rewritten to get value X_C	Rocks are not uniform in geomechanical properties. Various geological properties also vary within rock mass. This has impact on fragment size distribution which may not be uniform for different fraction of fragment distribution.e.g X_{50} may not be correlated with X_{20} or X_{80} with heterogeneous rock mass.
Cunningham (1987)	$n = (2.2\text{-}14\frac{B}{D})[\frac{1+S/B}{2}]^{0.5}\left(1-\frac{W}{B}\right)\left(\frac{L}{H}\right)$ ......(5) D = Hole diameter in mm, W= standard deviation in drilling in 'm'	Through various experimentation and investigations, Cunningham (1987)[8] reported that uniformity index to be 0.75 to 1.5. Value of 1 is preferable.
Morin and Ficarazzo (2006)[9]	Monte Carlo simulation based on Kuz–Ram model : Input parameters for Marlo Carlo simulation are UCS, elastic modulus, JPS, JD, JDD, dip direction of bench face, drilling accuracy.	Adequate field data required for testing simulation.
Gheibie et al., (2009) [10]	Modiified Kuz Ram Model $n = (2.2\text{-}14\frac{B}{D})\left(1-\frac{W}{B}\right)\sqrt{(\frac{1}{2}+\frac{s}{2B})} \times (0.1 + abs\,(\frac{BCL-CCL}{L}))^{0.1}\left(\frac{L}{H}\right)$ (6) L is the total charge length (m). Modification to Eq (6) where two different types of explosive used in single hole- bottom and column	Rock mass is not uniform and homogeneous across rock mass in different direction in terms of physical and mechanical properties. Blastability factor is considered as rock factor which also depends on subjective rock

	charge is as under: n=(2.2-14BD)(1-WB)(12+S2B)×(0.1+abs(BCL-CCLL))0.1(LH) (7) BCL= Bottom Charge Length in 'm' CCL= Column Charge Length in 'm' For staggered pattern equation to be multiplied by 1.1 The Rosin–Rammler curve is determined by the value of n $X_m = 0.073\ BI\ (\frac{V_o}{Q_e})^{0.8}\ Q_{e^{1/6}})(\frac{S_{anf_o}}{115})^{-19/30}$ (8) $n' = 1.88 * n * BI^{-0.12}$ (9)	properties.
Cunningham, (2005)[11]	$X_{50} = AA_T K^{-0.8} Q^{1/6} \left(\frac{115}{RWS}\right)^{720} C(A)$ (10) $n = n_s \sqrt{\left(2 - \frac{30B}{d}\right)} \sqrt{\left(\frac{1+S/B}{2}\right)} \left(1 - \frac{W}{B}\right) \left(\frac{L}{H}\right)^{0.3} C(n)$ (11) Where, 'A_T' - timing factor, which is applied to Equation 10 as a multiplier, and incorporates the effect of interhole delay on fragmentation, 'C(A)' a correction factor for the rock factor, 'n_s' is the uniformity factor governed by the scatter ratio. 'C(n)' is a correction factor for the uniformity index.	

Table 1: Empirical equations for prediction of blast fragmentation

The empirical equations are derived with certain assumptions that rock mass properties are uniform throughout. However, there is difference in aeromechanical properties which vary across rock mass. Blast ability index which is considered in modified Kuz Ram Model, where geological properties are subjective in nature. Quantitative values are given for each type of rock properties which may not be behave in the same manner actual in the field. Controllable factors are blast design and explosives. In blast design, ratio of various parameters does have impact on rock mass classification. There are also other factors which are delay demining, maximum charge per delay, loading density of explosives. The prediction of mean rock fragmentation due to blasting is always necessary in mining for planning downstream operation. Alternative method of predicting rock fragmentation is described in subsequent sections.

Recently, artificial intelligent (AI) techniques such as artificial neural networks (ANNs) have been widely-developed to solve problems in civil and mining engineering especially rock fragmentation problem (e.g., Mohamad et al. 2012[12]; Shams et al. 2015[13]; Saghatforoush et al. 2016[14]; Khandelwal and Jahed Armaghani 2016[15]; Hasanipanah et al. 2016b[16]; Armaghani et al. 2017[17]; Faraji Asl et al. 2017[18]). However, such tools have several limitations such as low learning speed and falling into local minima (Lee et al. 1991)[19]. As mentioned in literatures, using efficient optimization algorithms (OAs), these limitations can be overcome. Various OAs like particle swarm optimization (PSO), imperialism competitive algorithm (ICA) and genetic algorithm (GA) can be applied to solve continuous and discontinuous problems. Based on powerful ability of global search of these OAs, weights and biases of an ANN network can be determined in order to improve its performance prediction. In this study, a new hybrid model of ICA-ANN is developed to predict rock fragmentation and then in order to show its capability, a pre-developed ANN model is also introduced and compared.

2. Methods

2.1. Artificial neural network (ANN)

The ANN is a tool to model the complex systems in approximation problems such as medicine, finance and engineering. ANN is a data processing analysis system making a simulation of the structure and functions of human brain. It is an extremely interconnected multilayer structure including a large number of neurons. This network is enable to recognize similarities especially when they are presented with new input terms after properly predicting the proposed output pattern. The ANN is generally applicable as an alternative for some complex statistical analysis techniques such as auto correlation, trigonometric, multivariable regression, linear regression, and so on. It is well established a network can be defined using three basic components known as; (i) transfer function, (ii) network architecture, and (iii) learning law (Kosko 1992)[20]. These components are considered in order to select the most appropriate model for a given problem(s). Up to now numerous algorithms have been suggested to train the neural networks, among which the feedforward neural networks (FFNN) and back-propagation (BP) algorithm is known as the most reliable and accurate technique (Moayedi and Jahed Armaghani 2017)[21]. For instance, BP can solve predictive complex geotechnical problems; it makes back-propagation so popular among all existing algorithms for training ANN. The FFNN are the most common neural networks consisted of multiple hidden layers containing weight matrices, bias vectors and nonlinear transfer functions. Using such a network it is possible to find nonlinear complicated relations between inputs and output data sets via a training procedure. The neural networks extracted relations are not exact and there is always an error between the networks estimated data and real data. The components of weight and bias are tunable constants which should be tuned to minimize the network error. The process of tuning of these constants is called training of network. The act of training is similar to an optimization process. Various mathematical approaches are used to train the neural networks. Most of these approaches are basically analytical such as Levenberg Marquardt (LM), Bayesian regularization (BR), BFGS quasi-Newton (BFG) etc. LM approach is used for batch training of the networks in this paper.

2.2 Imperialist competitive algorithm (ICA)

Imperialist competitive algorithm (ICA) is firstly proposed by Atashpaz-Gargari and Lucas (2007)[22] in order to be used in optimization problems. It is a global search population-based system that its process is similar to many other evolutionary algorithms. ICA gets started with an initial population (or candidate solutions), that with the ICA consists of countries. These countries are then divided into two categories: imperialists (i.e. some of the best countries) and colonies (i.e. the remaining countries) (see Figure 1). To generate empires the colonies are distributed among the imperialists, as determined by a pre-defined criterion, according to their relative strength. The empires then compete with each other in order to expand their power and control more colonies. Therefore, as a result of looping this competition, stronger empires expand their power by taking possession of weak colonies located in weaker empires. This process is continuously repeated until the process stopped after being satisfied by a pre-defined stopping criterion. A detailed description of the designed steps in ICA algorithm alone is widely available in literature. The readers are recommended to see Ghorbani and Jokar (2016) [23] and Al Dossary and Nasrabadi (2016)[24] for more detail of ICA.

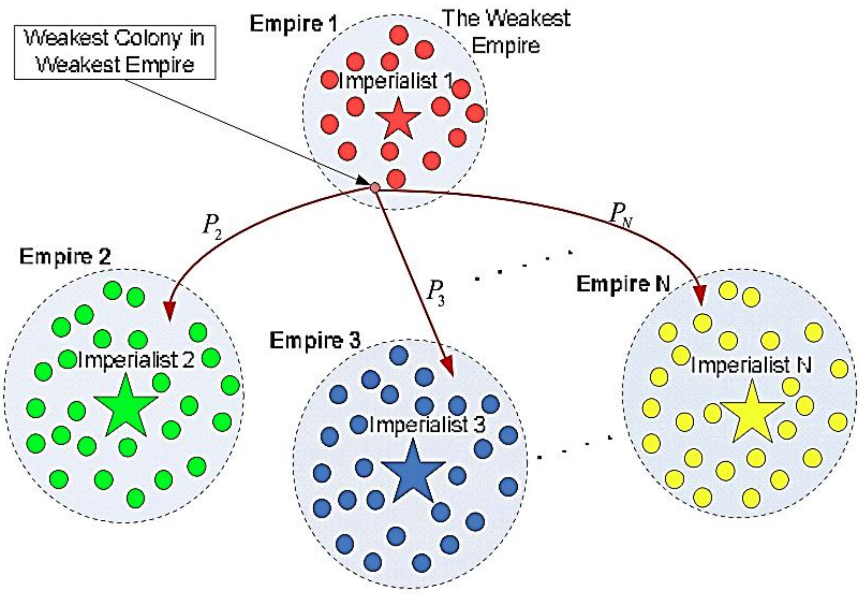

Figure 1. Imperialistic competition to take possession of weakest colony

2.3. Combination of ICA-ANN

Many attempts have been conducted to improve the performance of ANNs through the use of OAs like ICA, PSO and GA in engineering problems. Since BP is a local search learning algorithm, the optimum search process of ANN may fail and return unsatisfied solution. OAs can be utilized to adjust the bias and weight of the ANN to improve its performance level. Regarding the local minimum in ANN system, there is normally more probability of convergence, while OAs are able to discover a global minimum. So, hybrid systems like ICA-ANN enjoy search properties of all ANN and ICA techniques. In search space, ICA searches for global minimum, and then ANN employs it for finding the best results of the system.

3. Case Study and Data Collection

The selected aggregate quarry consists of limestone deposit. Limestone can be divided into 3 unite, first is a thin bedded argillaceous limestone, second is an argillaceous limestone, and the last one cannot bounded is a massive dark color limestone. Structure geology main fault is in NE-SW direction at block D and main anticline recumbent folding type was across middle of project area. Limestone in these resources was re-crystallized due to metamorphism rocks.

The 1st layer (D) is the overburden having thickness of 2 to 5 m. The 2nd layer (C). is highly weathered having thickness of 2 to 10 m. The 3rd layer (B) is slightly weathered having thickness of 2 to 30 m. The 4th layer (A) as massive limestone having thickness of 1 to 100 m. 10 bore holes were drilled in 2 sq KM Area. 100 m each 10 numbers of bore holes were drilled. Various rock types maximum (Max) and average (Av.) thickness are given below: Top Soil (Max: 0.60 M, Av.: 0.32 m) ; Weathered (Max: 17.50 M, Av. : 3.67 m); Shear zone (Max: 26.10 M, Av. : 8.51 m); Thick bedded Argilaceous (Max: 15.60 M, Av. : 2.44 m);Thick bedded Limestone (Max: 97.00 M, Av. : 65.60 m); Thick bedded Argillaceous (Max: 65.60 M, Av. : 15.87 m). Cavity varies from nil to maximum 12.10 m with average of 1.62 m per borehole. RQD% varies from minimum of 50.8% to maximum of 90.02% with average of 76.09%.

Limestone quarry production is increased from 2.5 MTPA to 5 MTPA. Mining equipment consist of 2.2 Cu m excavators, 30 T capacity dump trucks, 76 mm / 102 mm diameter drills. Figure 2 shows a view of working quarry with various equipment. Primary crusher maximum permissible rock is 800 mm. With increased production, well fragmented limestone has become essential for achieving optimum production capacity of each equipment such as excavator, dump truck and crusher. Achieving mean fragment size X50 as 0.3 m or less is essential to achieve optimum production form each group of equipment.

Figure 2. Working limestone quarry at Thailand

Hence, literature review was done of various parameters which are considered by various researchers to predict mean blast fragment size. Fragmentation is controlled by properties of rock mass and geological discontinuities, explosives used and delay interval between hole to hole, blast-hole diameter, burden, spacing, bench height, length of stemming, drill hole deviation and alignment, blast-hole pattern staggered or rectangular or square, drill hole sub drilling(Ash, 1968[25]; Hustrulid, 1999[26]). Fragmentation due to blasting depends upon certain controllable parameters such as blast design and explosives being used. Uncontrollable parameters are related to rock mass properties –

geomechanical strength, in situ block size.

Total volume of rock to be blasted which is a product of bench height, spacing, burden and number of holes. Explosives is distributed across rock mass through blast holes which breaks rock mass into smaller fragmentation. Minimum and maximum permissible limit of bench height and burden depends upon blast-hole diameter. On the other hand, blast-hole diameter is selected based on environmental limitation such as tolerable ground vibration, air over pressure and flyrock, fragmentation desired. With increase in hole-diameter, cost of drilling and blasting is lowered. Maximum hole-diameter is restricted by environmental factors and mean blast fragmentation which can be maximized without lowering capacity of down stream operation. Minimum size hole makes limit of total blasted volume in a single blast. Previous studies reported that based on studies by CMRI and NIRM, India that maximum hole diameter in mm can be 16.66 times bench height +50 and minimum hole can be 10 times bench height (bench height is in m). For effective blasting, burden to be 15 to 40 times hole diameter (Bhandari, 1997)[27]. As per research findings by Konya and Walter (1990)[28], stiffness ratio to be 2 to 4 where ratio of bench height to burden is known as stiffness ratio. Based on fragmentation desired from in situ rock mass and explosives used, ratio of spacing to burden to be in the range of 1 to 2. Length is stemming is kept in the range of 0.7 to 1 times burden. With decrease in stemming length, boulder generation is reduced from stemming portion. However, the risk of flyrock is increased with reduction of stemming length. It is observed that from research studies that blast fragmentation can be correlated with various ratios (B/D, H/D, S/B, T/B) instead of single parameter (Chakraborty et al., 2004[29]; Faramarzi et al., 2013; Kulatilake et al., 2010[30], 2012[31]).

In blasting process where explosives energy transforms in situ rock mass distribution to blasted rock fragmentation (Lu and Lathan and, 1999)[32]. Overall ratio of explosives consumed in kg to total in situ blasted rock mass in cu m is known as powder factor. Maximum charge per delay (MC) is parameter which indicates maximum energy released instantaneously. Powder factor and maximum charge per delay represent how explosives energy is transforming in situ rock mass to blasted rock fragmentation. Powder factor is important parameter in predicting mean fragment size according to many scholars (e.g., Chakraborty et al., 2004; Saliu and Akande 2007[33]). Research study by Monjezi et al. (2009)[34] and Faramarzi et al. (2013)[35] showed that MC is crucial to predict blast fragmentation.

Total eight parameters consisting of block size (XB), RQD%, maximum charge per delay (MC), powder factor, (B/D) burden to hole diameter ratio, (S/B) spacing to burden ratio, (H/B) ratio of bench height to burden, (T/B) stemming height to burden ratio were considered as inputs to predict rock fragmentation. The system output was anlaysed by taking photograph of each blast muck pile comparing with known size of object (see Figure 3). Mean fragment size and rock fragmentation distribution is determined through image analysis software (see Figure 4). Table 2 presents range of input and output parameters used for AI modeling of this study. It should be noted that a total number of 111 datasets were prepared in order to develop AI techniques.

Figure 3. Blast fragment muck pile

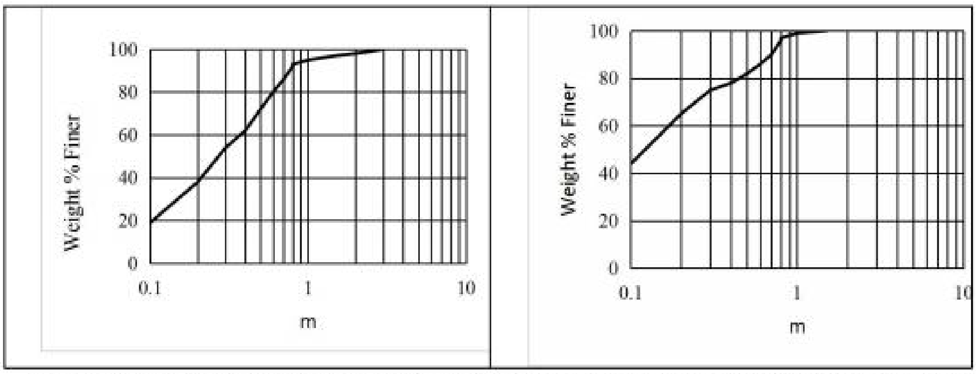

Figure 4. Image analysis of blast muck pile using blast muck pile (a) In situ block size = 0.8 m (b) In situ block size = 0.1 m

Parameter	Unit	Symbol	Category	Range
Block Size	m	X_B	Input	0.1-1.2
Rock quality designation	%	RQD	Input	42-87
Maximum charge per delay	kg	MC	Input	74.8-500
Powder factor	Kg/m^3	PF	Input	0.1-0.47
Burden to hole diameter ratio	-	B/D	Input	0.032-0.042
Spacing to burden ratio	-	S/B	Input	1-1.3
Ratio of bench height to burden	-	H/B	Input	1.33-4.07
Stemming height to burden ratio	-	T/B	Input	0.6-1
Rock fragmentation	m	Fr	Output	0.13-0.28

Table 2 Range of input and output parameters used for AI modeling of this study

4. The Developed AI Models

4.1 ANN

At the beginning of ANN modelling, as mentioned by Liou et al. (2009)[36], the developed datasets should be normalized to simplify the design procedure using the following equation:

Xnorm = (X – Xmin) / (Xmax-Xmin)(1)

where X and Xnorm are the measured and normalized values, respectively. Xmax and Xmin are the maximum and minimum values of the X.

Then, for developing and evaluating the model, all datasets should be divided into training and testing parts, respectively. A range of (20%-30%) of whole datasets was recommended for testing datasets in the investigation conducted by Nelson and Illingworth (1991)[37]. So, in this study, 20% of whole datasets (111 datasets) were considered as testing datasets. Many investigations reported the successful utilization of LM training algorithm (Ornek et al. 2012)[38]. Because of that, in this study, the mentioned algorithm was utilize to design ANN. Additionally, it is well-established that an ANN with one hidden layer can approximate any continuous function. For determining the No. of hidden node, Hornik et al. (1989)[39] stated that the maximum number of hidden node is $\leq 2\times$ Ni + 1, where Ni is number of input layers. Based on this equation and Ni = 8, it seems that a range of 1 to 17 can be solved rock fragmentation problem. A series of ANN models were analyzed and their results were evaluated according to root mean square error (RMSE) and coefficient of determination (R2) values. RMSE and R2 were selected as one of the most popular performance indices in order to evaluate predictive models. The results showed that the architecture of $8\times 10\times 1$ receives lowest RMSE and highest R2 values. Therefore, a model with hidden node of 10 was used and introduced for the selected ANN model and this architecture will be used for all hybrid models too. RMSE values of (0.090 and 0.101) and R2 of (0.813 and 0.819) were obtained for training and testing datasets of the best ANN model in estimating rock fragmentation. Evaluation of the best ANN model will be discussed later.

4.2 ICA-ANN

In modelling of ICA-ANN, the most important factors on ICA should be investigated and subsequently designed. The most important factors on ICA are Ncountry (number of country), Nimp (number of imperialism) and Ndecade (number of decade). Various values of Ncountry have been utilized to approximate problems of geotechnical engineering. Therefore, it seems that a parametric study is needed to obtain the proper Ncountry. Therefore, a series of ICA-ANN analyses were conducted using various Ncountr ranging from 25 to 400. In these models, Ndecade equal to 500 and Nimp equal to 5 were utilized. Figure 5 shows the results of analysis based on RMSE. As a result, Ncountry = 250 receives the lower error compared to other utilized Ncountry values. In addition, as shown in Figure 5, RMSE values are constant for all Ncountry after number of decade equal to 300. Therefore, a hybrid ICA-ANN model with Ncountry = 250, Ndecade = 300, Nimp = 5 and network architecture of $8\times 10 \times 1$ is introduced for rock fragmentation prediction. ICA-ANN network results were as RMSE of (0.047 and 0.047) and R2 of (0.949 and 0.941) for training and testing datasets, respectively. More discussions concerning the best ICA-ANN model for prediction of rock fragmentation are given in the next section. It is important to note that all AI models in the present research were constructed using MatLab version 7.14.0.739 (Demuth and Beale, 2000).[40]

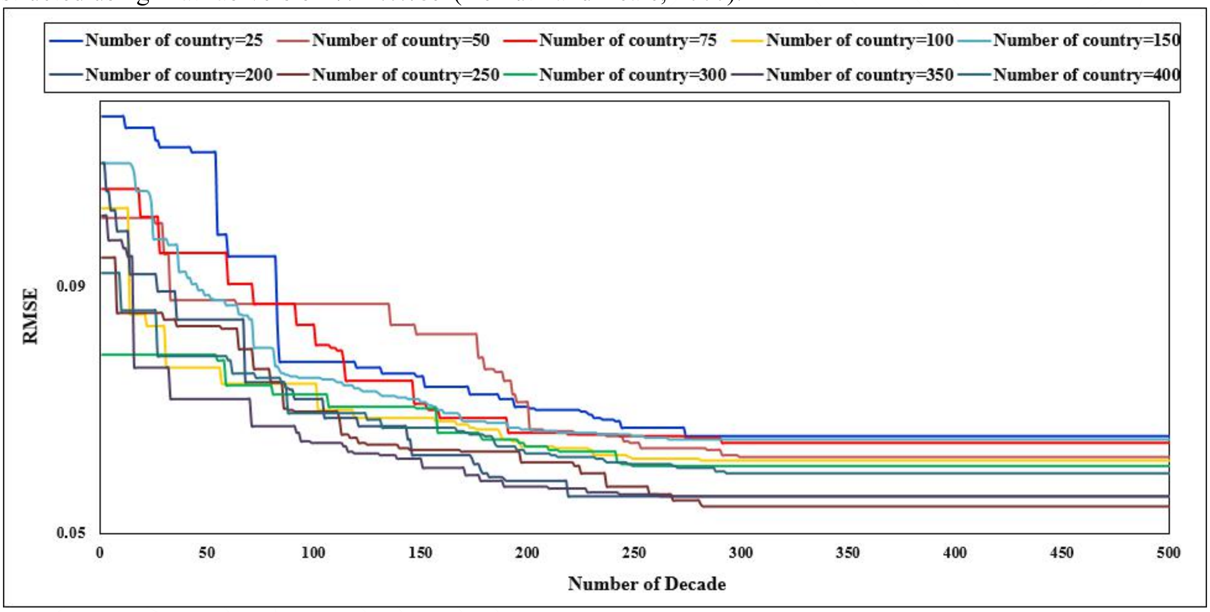

Figure 5. RMSE values for various $N_{country}$ in predicting rock fragmentation

5. Model Evaluation

Evaluation of the obtained results in predicting rock fragmentation resulting from blasting is discussed in this section. In this regard, the selected performance indices are R2, RMSE and variance account for (VAF) which their equations can be seen as follows:

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

$$VAF = \left[1 - \frac{var\,(y-y')}{var\,(y)}\right] \times 100 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y-y')^2} \quad (4)$$

where y and y' are the predicted and measured values, respectively, $\tilde{y}$ is the mean of the y values and N is the total number of data. The model will be excellent if R2 = 1, VAF = 100 and RMSE = 0.

After a precise evaluation, higher performance capacity was provided by hybrid model in terms of all VAF, RMSE and R2 values of both training and testing phases (see Table 3). RMSE values of (0.090 and 0.047) and (0.101 and 0.047) were obtained for training and testing of ANN and ICA-ANN models, respectively. In addition, VAF values near to 100 (94.573, and 94.082 for train and test of ICA-ANN, respectively) were achieved for a new developed hybrid model. These results demonstrated that minimum system error can be achieved advancing hybrid model. Figures 6 to 9 shows predicted rock fragmentation values together with their actual values for ANN and ICA-ANN models. Both of training and testing datasets are showed in these figures. As shown, the developed hybrid model gives higher level of capability in prediction of rock fragmentation. The developed predictive models could be used for similar condition in the future.

Model	Performance Index					
	R^2		RMSE		VAF	
	Train	Test	Train	Test	Train	Test
ANN	0.813	0.819	0.090	0.101	80.797	81.290
ICA-ANN	0.949	0.941	0.047	0.047	94.573	94.082

Table 3. The obtained results of intelligent methods

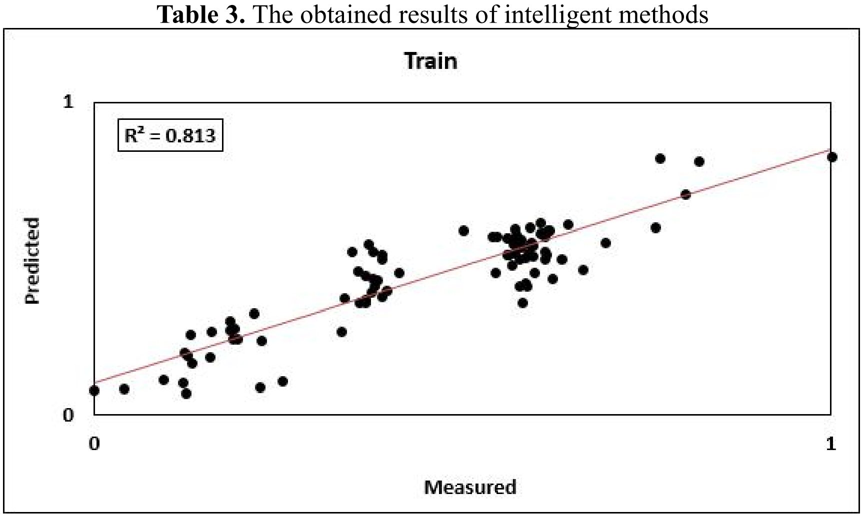

Figure 6. Training dataset results obtained by ANN model

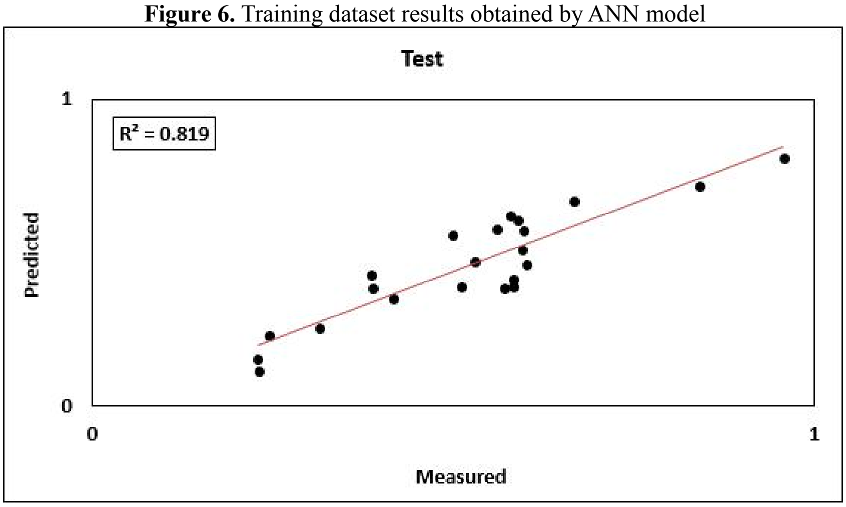

Figure 7. Testing dataset results obtained by ANN model

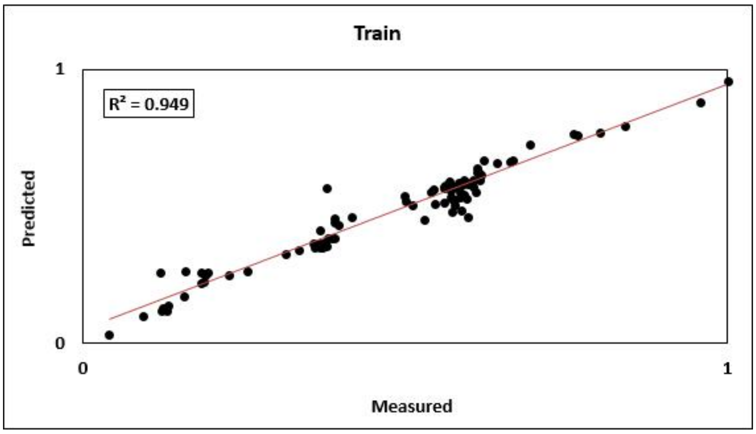

Figure 8. Training dataset results obtained by ICA-ANN model

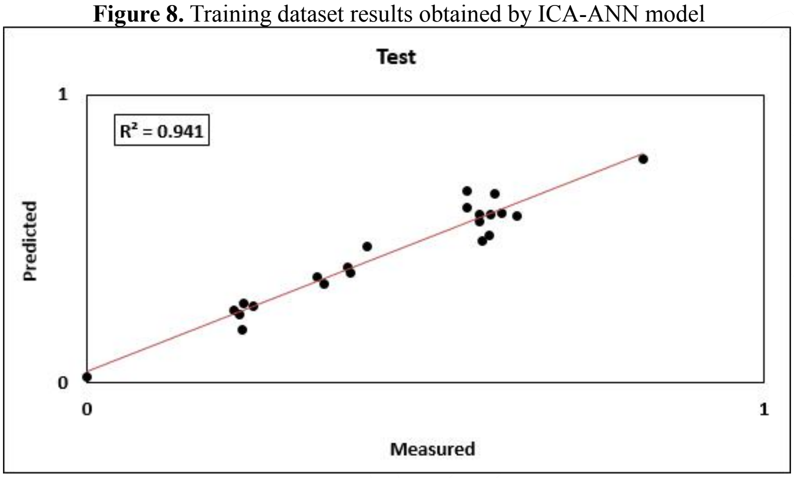

Figure 9. Testing dataset results obtained by ICA-ANN model

6. Conclusions

Many blasting operations were monitored and the most effective parameters on rock fragmentation were measured and used to develop AI techniques. Two intelligent models i.e., ANN and ICA-ANN were considered and developed for prediction of rock fragmentation. With respect to the related previous studies, the most important parameters of ICA were identified and determined in the present study. To estimate rock fragmentation, many ICA-ANN and ANN models were applied and the best ones among them were selected to be introduced in this study. Considering the most famous performance indices, all proposed models were carefully evaluated. After evaluation, it was found that in terms of both train and test, the ICA-ANN model receives better results in solving problem of rock fragmentation. R2 values of (0.949, and 0.813) and (0.941 and 0.819) were obtained for training and testing of ICA-ANN and ANN models, respectively. In addition, VAF values near to 100 (94.573, and 94.082 for train and test, respectively) were achieved for a developed ICA-ANN hybrid model. Note that, the AI models of this study cab be used in similar condition with caution.

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