

# Developing a new hybrid-AI model to predict blast-induced backbreak

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**Abstract** Drilling and blasting is the predominant rock excavation method in mining and tunneling projects. Back-break (BB) is one of the most undesirable by-products of blasting and causing rock mine wall instability, increasing blasting cost as well as decreasing performance of the blasting. In this research work, a practical new hybrid model to predict the blast-induced BB is proposed. The model is based on particle swarm optimization (PSO) in combination with adaptive neuro-fuzzy inference system (ANFIS). In this regard, a database including 80 datasets was collected from blasting operations of the Shur river dam region, Iran, and the values of four effective parameters on BB, i.e., burden, spacing, stemming and powder factor were precisely measured. In addition, the values of the BB for the whole 80 blasting events were measured. The accuracy of the proposed PSO-ANFIS model was also compared with the multiple linear regression (MLR). Median absolute error, coefficient of determination ( $R^2$ ) and root mean squared error, as three statistical functions, were used to evaluate the performance of the predictive models. The results achieved indicate that the PSO-ANFIS

model has strong potential to indirect prediction of BB with high degree of accuracy. The  $R^2$  equal to 0.922 suggests the superiority of the PSO-ANFIS model in predicting BB, while this value was obtained as 0.857 for MLR model.

**Keywords** Blasting · Back-break · PSO-ANFIS · MLR

## 1 Introduction

Blasting operation is one of the most widely methods to remove the rock mass in open-cast mines. Although, the main goal of blasting is rock fragmentation, only 20–30 % of the produced energy is applied for this goal and the remained energy is dissipated to create environmental side effects such as ground and air vibration, back-break (BB) and fly-rock [1–6]. BB has several adverse effects such as rock mine wall instability, poor fragmentation and high dilution [7–9]. Therefore, precise prediction of BB is an important criterion for restricting the environmental effects of blasting. Based on literature, the effective parameters on the BB can be divided into two main groups: blast design parameters and rock mass properties. Blast design parameters or controllable parameters can be changed by the blasting engineers [10–13]. The burden, spacing, stemming, type of explosive material, blast-hole diameter and depth, powder factor and sub-drilling are all controllable parameters. Some of the controllable parameters are displayed in Fig. 1. In the second group, rock mass properties or uncontrollable parameters, such as tensile and compressive strength of rock, cannot be changed by the blasting engineers [14, 15]. Based on previous relative surveys, various models e.g., the genetic programming (GP), the artificial neural network (ANN), the support vector machine (SVM), the adaptive neuro-fuzzy inference system (ANFIS), the multiple regression (MR) and the Monte Carlo (MC)

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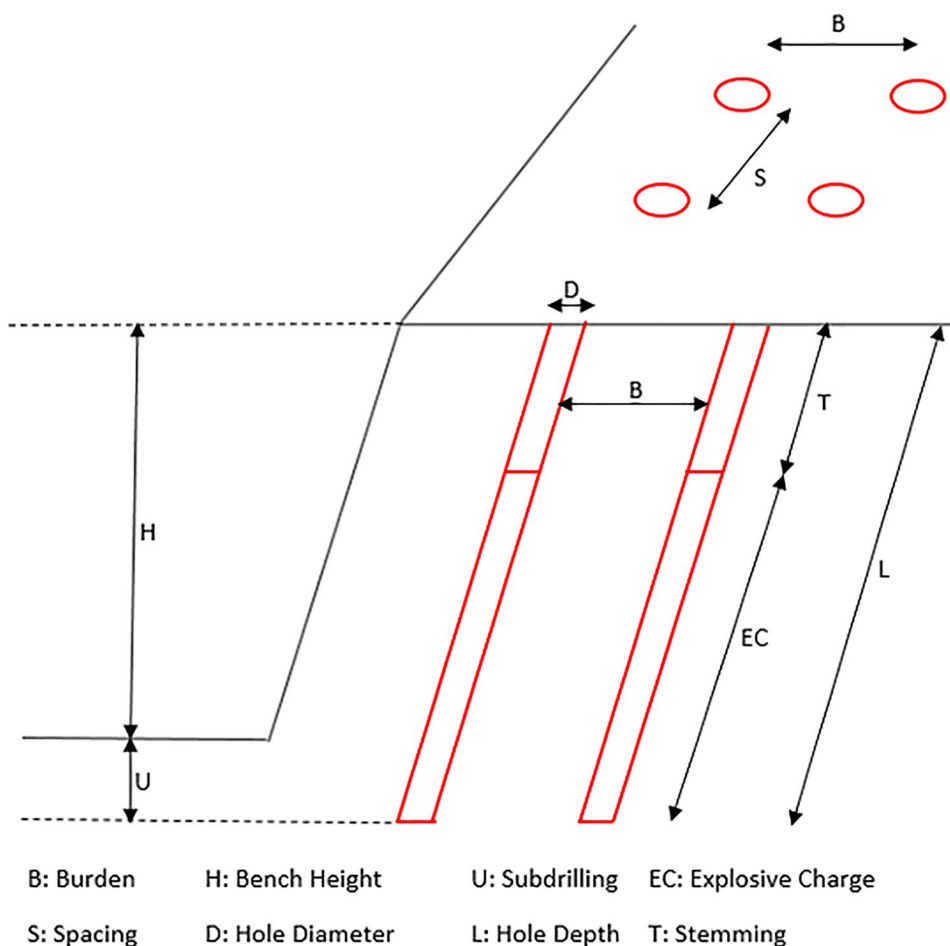
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**Fig. 1** Several controllable parameters of blasting



simulation were developed to predict blast-induced BB. Esmaili et al. [9] developed ANN, ANFIS and MR to predict blast-induced BB in Sangan iron mine, Iran. They indicated that ANFIS can be a more precise model than ANN and MR. A comprehensive study for the prediction of BB in Soungun iron mine, Iran, was presented by Khandelwal and Monjezi [10] using SVM and multivariate regression analysis (MVRA). Based on their results, the SVM with  $R^2 = 0.98$  can predict BB better than MVRA with  $R^2 = 0.89$ . In the other study, ANN and regression model were established to predict BB in the study conducted by Monjezi et al. [11]. They used ten parameters, i.e., burden, spacing, bench height, uniaxial compressive strength, powder factor, water content, blast-hole diameter, charge per delay, stemming, and specific drilling as input parameters. Their results demonstrated capability of the ANN in predicting the BB compared to regression model. Also, they concluded that the burden was the most influencing parameter in the studied case. Ghasemi et al. [16] employed ANFIS and regression tree (RT) for BB prediction. Their datasets were collected from Sungun Copper Mine (SCM), in Iran. Finally, it was found that the ANFIS can be performed for the BB prediction with greater degree of confidence in comparison with RT. In the other research at

Sungun copper mine, Shirani Faradonbeh et al. [13] proposed GP and non-linear multiple regression to predict BB. Based on their results, GP can be introduced as a powerful tool in the field of BB prediction. Table 1 gives recently developed models and their input parameters for estimating BB. In this paper, a new combination of ANFIS and particle swarm optimization (PSO) is proposed to develop a powerful model for prediction of BB at Shur river dam, Iran. To demonstrate applicability of the proposed PSO-ANFIS model, multiple linear regression (MLR) was also developed and then, a comparison was made between the obtained results. Note that, the PSO-ANFIS model has been proposed for predicting aims in several areas of research (e.g. [17, 18]). Nevertheless, as far as authors know, the PSO-ANFIS is a new predictor in the field of BB prediction.

## 2 Materials and methods

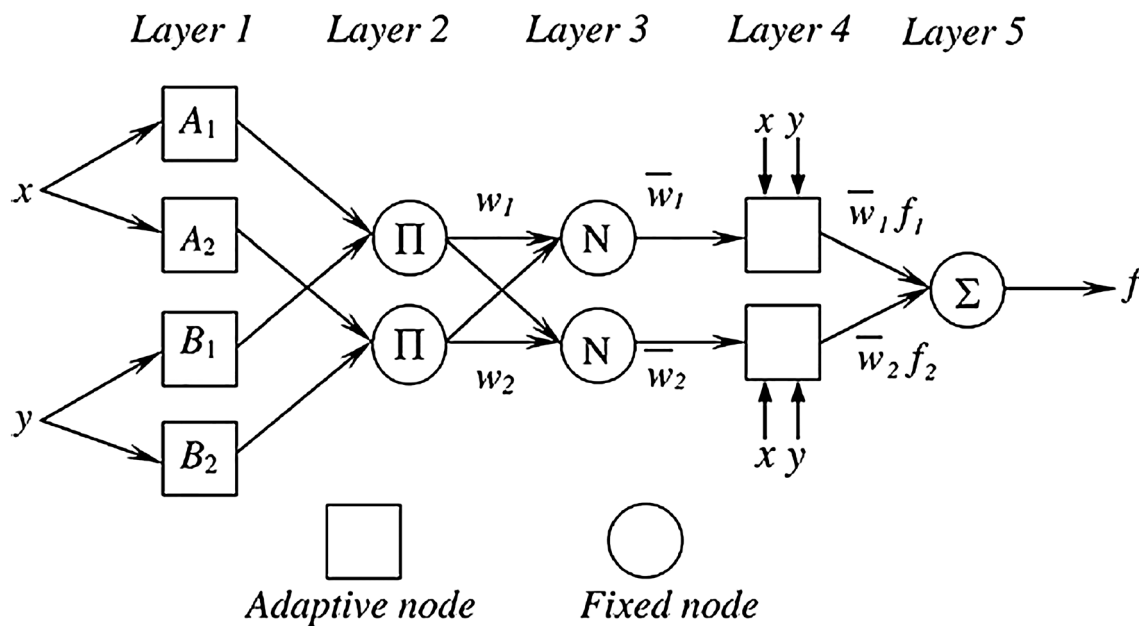
### 2.1 ANFIS model

The ANFIS, as a unified prediction model, was first introduced by Jang [19] and utilizes benefits of both ANN and fuzzy

**Table 1** Recently-developed models and their input parameters for estimating BB

References	Technique	Input parameter	No. of dataset	$R^2$
Monjezi et al. [48]	GA-ANN	$D, L, B, S, ST, SC, SD, C, RMR$	195	0.96
Esmaeili et al. [9]	ANN, ANFIS	$SR, ST, SC, RD, N, CLR, S/B$	42	ANN = 0.92 ANFIS = 0.96
Mohammadnejad et al. [8]	SVM	$B, S, L, SD, ST, SC$	193	0.92
Sayadi et al. [49]	ANN	$B, S, L, ST, SC, SD$	103	0.87
Ebrahimi et al. [8]	ANN	$B, S, ST, L, SC$	34	0.77
Shirani Faradonbeh et al. [13]	GP	$B, S, ST, SC, SR$	175	0.98

*HL* hole length, *S* spacing, *B* burden, *ST* stemming, *SC* specific charge, *SD* specific drilling, *SVM* support vector machine, *C* charge per delay, *D* hole diameter, *HD* hole depth, *RD* rock density, *B/S* burden to spacing, *N* number of row, *GA* genetic algorithm, *RMR* rock mass rating, *SD* sub-drilling, *FIS* fuzzy interface system, *GP* genetic programming



**Fig. 2** An ANFIS architecture (Jang et al. [30])

inference system (FIS) techniques in a hybrid model. The advantage of FIS are capability of decision-making, despite the dominant uncertainty, incomplete and inaccuracy of real-world problems [20, 21]. Also, ANN algorithm is capable to adapt its abilities of learning. The ANFIS applies a hybrid learning model including gradient descent and least-squares algorithms. The application of ANFIS model to estimate the environmental side effects induced by mine blasting, is investigated in some studies [22–27]. The results demonstrated that the ANFIS is an acceptable and reliable model in this field.

Figure 2 shows the ANFIS architecture with two inputs and five layers. In this structure, the Sugeno fuzzy type is used as FIS. Two rules of fuzzy “if-then” can be presented as follows [28]:

$$\text{Rule 1 : If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \quad (1)$$

$$\text{Rule 2 : If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \quad (2)$$

where  $p_1, q_1, r_1, p_2, q_2, r_2$  are the function parameters of output ( $f$ ). Also,  $A$  and  $B$  are specified as the membership functions for inputs ( $x$  and  $y$ ). As it can be seen that in Fig. 2, a five-layer ANFIS with one output and two inputs can be explained in the following lines [29–31]:

*Layer 1 (fuzzification layer)* all nodes are considered as an adaptive node.

*Layer 2 (product layer)* calculation of the firing strength.

*Layer 3 (normalized layer)* the normalization is done according to Eq. 3.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2. \quad (3)$$

Layer 4 (defuzzification layer) each node is an adjustable node with the following node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i). \quad (4)$$

In Eq. 4,  $w_i$  is output of the third layer. Also,  $\{p_i, q_i, r_i\}$  are the parameter sets of  $\bar{w}_i$ 's node.

Layer 5 (output layer): system output is generated through sum of the incoming signals (see Eq. 5). As shown in Fig. 1, there is only one node in this structure.

$$O_{5,i} = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}; \quad i = 1, 2 \quad (5)$$

## 2.2 Particle swarm optimization (PSO)

Particle swarm optimization as a population based algorithm, was introduced by Kennedy and Eberhart [32]. The principal of the PSO are the social behavior and cognitive of swarm. The PSO has some advantages, namely the following [33–37].

1. Particle swarm optimization is a fast and easy algorithm to understand and implement.
2. Particle swarm optimization is an efficient optimization technique to maintain the diversity of the swarm.
3. In PSO, there are fewer parameters to adjust.

The PSO consists of a swarm of particles that search for the best position, including the best personal ( $p_{\text{best}}$ ) and global ( $g_{\text{best}}$ ) positions, based on its best solution [38, 39]. In the other words, during each iteration, each particle moves in the direction of its best  $p_{\text{best}}$  and  $g_{\text{best}}$  positions.

The velocity and position of a particle during its moving process can be formulated as follow:

$$V_{\text{new}} = w \times V + C_1 \times r_1 (p_{\text{best}} - X) + C_2 \times r_2 (g_{\text{best}} - X) \quad (6)$$

$$X_{\text{new}} = X + V_{\text{new}} \quad (7)$$

- $V$  and  $X$  represent current velocity and position of particles, respectively.
- $V_{\text{new}}$  and  $X_{\text{new}}$  represent new velocity and position of particles, respectively.
- $C_1$  and  $C_2$  are two positive acceleration constants.
- $w$  represents the inertial weight
- $r_1$  and  $r_2$  represent the random numbers in (0, 1)

Learn more about the PSO can be found in many studies (e.g. [40, 41]). In the past few years, many attempts have been done to highlight the application of PSO for solving problems

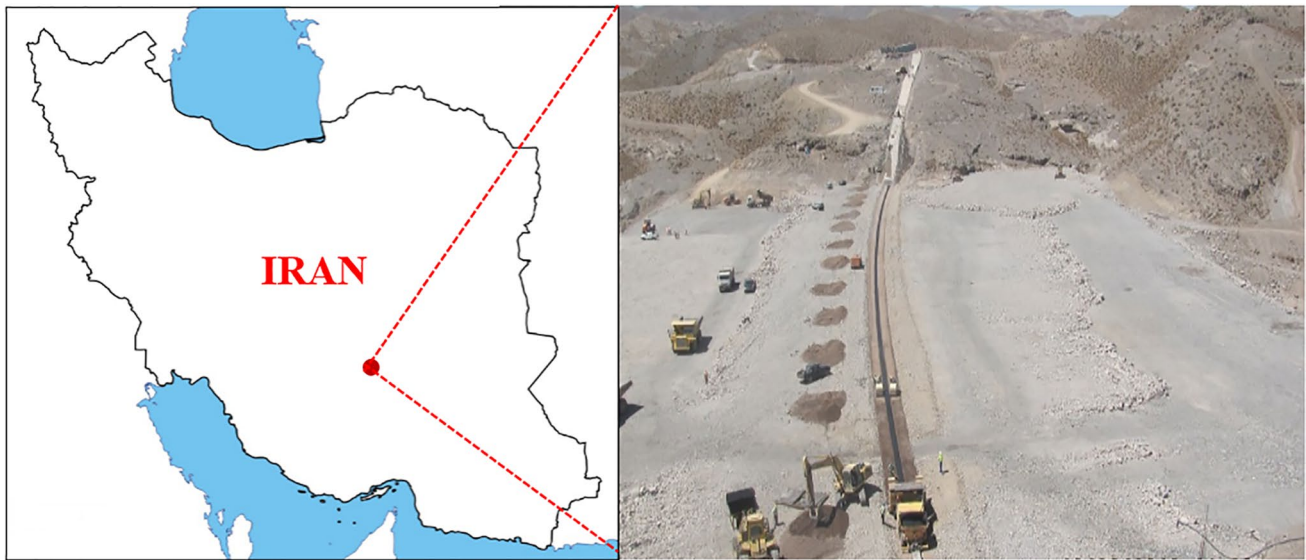
of rock and geotechnical engineering. Day by day the number of researches being interested in PSO increases rapidly. For instance, Kalatehjari et al. [42] used PSO and conventional methods to predict slope stability. They concluded that the PSO could perform better than the conventional methods individually. A combination of PSO and ANN for prediction of the ultimate bearing capacity ( $Q_u$ ) was proposed by Jahed Armaghani et al. [43]. They indicated the proposed PSO-ANN model can be used successfully for prediction of  $Q_u$ . Tonnizam Mohamad et al. [44] developed PSO-ANN model to predict the unconfined compressive strength (UCS) of soft rocks. Their result showed that the PSO can be used as a powerful algorithm to optimize the ANN.

## 3 Case study

The field study was conducted at Shur river dam region in Iran which situated near Sarcheshmeh copper mine. The Shur river dam is situated in the south of province Kerman, between  $30^{\circ}1'48''$  latitudes and  $55^{\circ}51'47''$  longitudes (see Fig. 3). Two mines, i.e., main and second mines were extracted to construct the Shur river dam. The mentioned mines were in the vicinity of the dam and drilling and blasting method was used in the extracting process. Wagon Drill Machine and ammonium nitrate fuel oil (ANFO) were used for drilling and blasting processes, respectively. In addition, the blast-holes were stemmed with fine gravels. As suggested above, BB is one of the most undesirable by-products of blasting. So, an extensive research program was carried out to predict blast-induced BB in the Shur river dam. In this regard, a total number of 80 blasting events were considered and the values of BB were measured. IN addition, the values of several influential parameters on the BB, i.e., burden ( $B$ ), spacing ( $S$ ), stemming ( $ST$ ) and powder factor ( $PF$ ) were measured. In this regard,  $B$ ,  $S$  and  $ST$  were measured by a tape meter. The  $PF$  was also obtained by division of the mean charge per blast-hole on the blast volume (burden  $\times$  spacing  $\times$  bench height) [12, 14]. To measure the BB, the horizontal distance between the pre-blast surveyed position of the last row of blast-holes and the crack with the maximum separation (critical crack) was considered as the BB, as suggested by Sari et al. [12]. Table 2 summarizes the range of measured parameters in this study. Furthermore, Figs. 4, 5, 6, 7 and 8 depict the frequency distributions of the  $B$ ,  $S$ ,  $ST$ ,  $PF$  and  $BB$ , respectively.

## 4 Prediction of BB

To develop the PSO-ANIFS and MLR models, the datasets have been divided into the following two groups: (1) training datasets. This is used to develop the mentioned

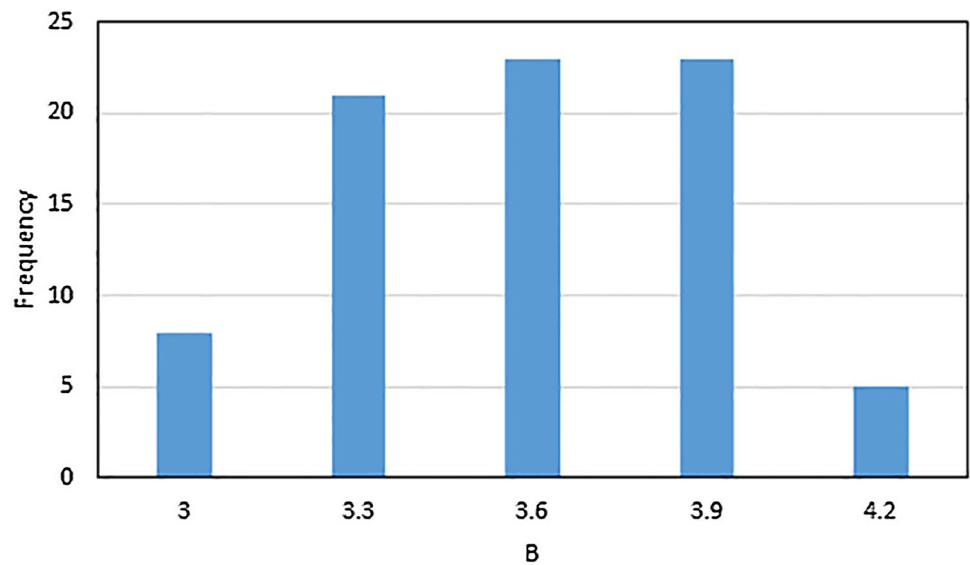


**Fig. 3** A view of Shur river dam region

**Table 2** The range of measured parameters in this research

Parameter	Symbol	Unit	Min	Max	Mean	SD
Burden	<i>B</i>	m	2.7	4.1	3.5	0.35
Spacing	<i>S</i>	m	3.4	5.3	4.3	0.46
Stemming	ST	m	1.8	3.4	2.7	0.4
Powder factor	PF	gr/cm <sup>3</sup>	152	217	183	16.36
Back-break	BB	m	3.8	5.6	4.5	0.35

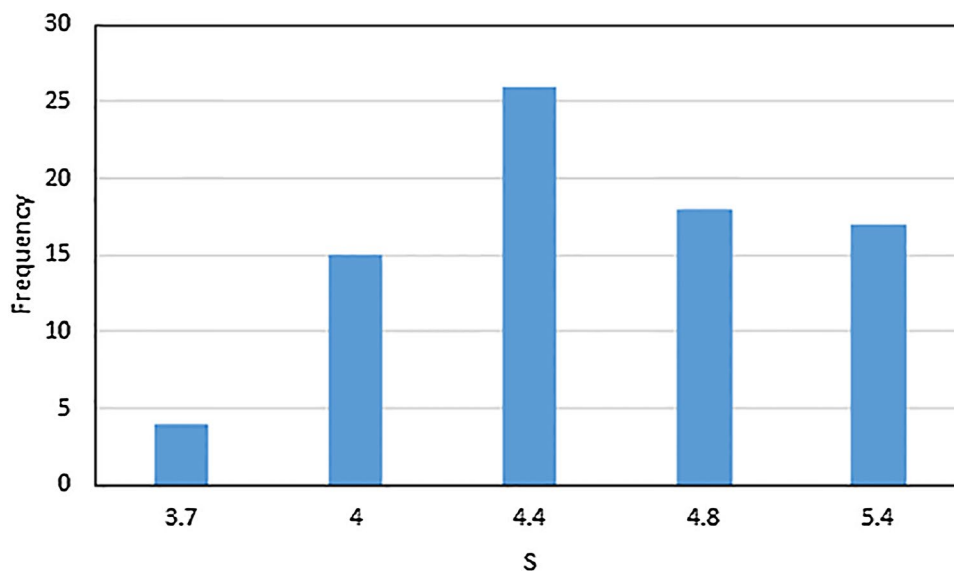
**Fig. 4** Frequency histogram of the measured burden



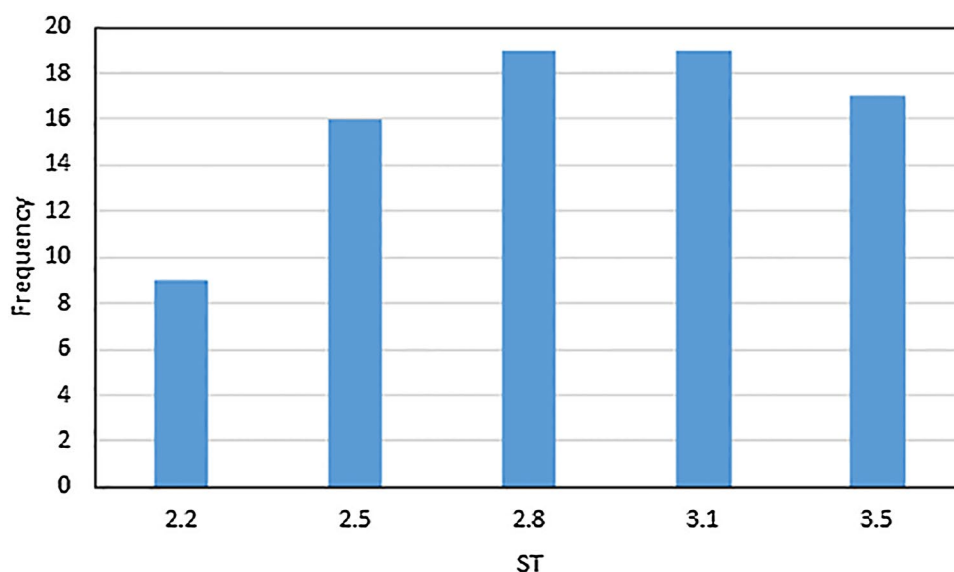
models. In this study, 80 % of whole datasets (64 of 80 datasets) were used as training dataset; (2) testing dataset. This is used to verify the developed models. The remaining 16 datasets have used as testing dataset. Using 80 and

20 % of whole datasets was recommended by Swingler [45] for training and testing purposes, respectively. In modeling, four effective parameters on the BB i.e., *B*, *S*, ST and PF were set as model inputs, while BB was set as model output.

**Fig. 5** Frequency histogram of the measured spacing



**Fig. 6** Frequency histogram of the measured stemming (ST)

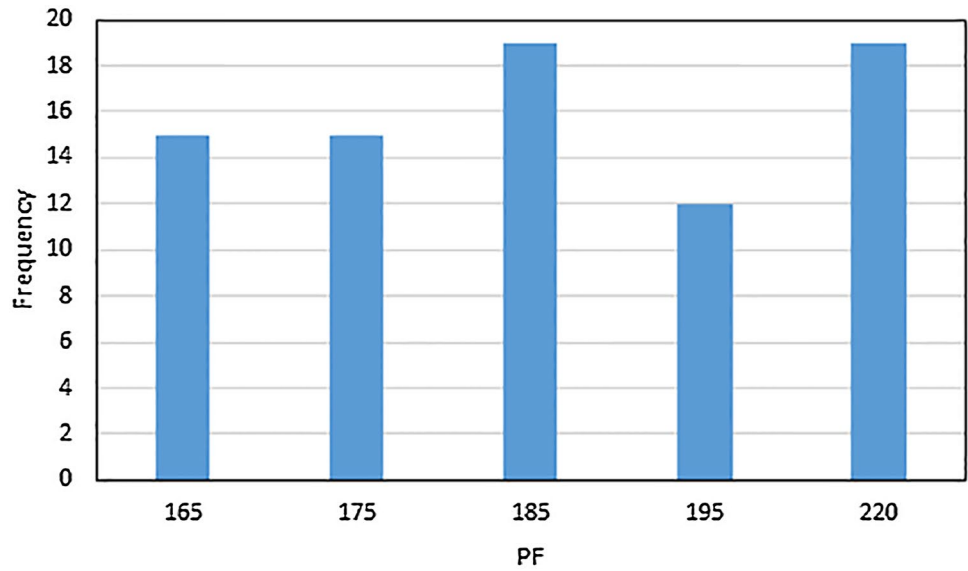


#### 4.1 Prediction of BB using PSO-ANFIS

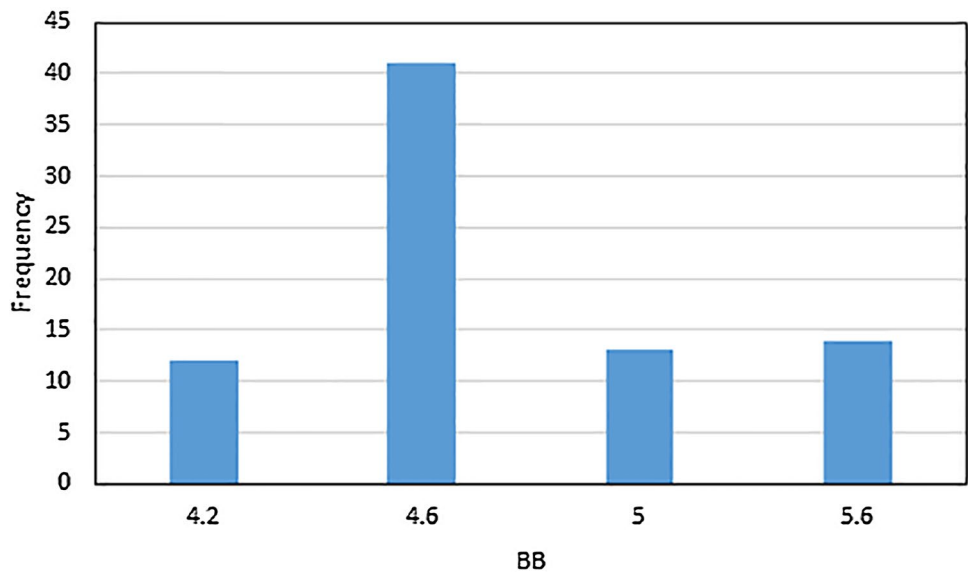
In this section, a new soft computing-based predictive model for predicting the BB is proposed. The proposed model is based on PSO and ANFIS models. In fact, the PSO optimizes values of ANFIS parameters using a population-based search. Hence, PSO was applied to train ANFIS for determining the optimal values of the ANFIS parameters. In the other words, the ANFIS provides the search space and employs PSO for finding the best solution by tuning the membership functions required to achieve lower error. For this goal, root mean square error (RMSE) is utilized as fitness function. The proposed PSO-ANFIS model was performed by writing a MATLAB code. In the modeling, B, S,

ST and PF were set as model inputs, while BB was set as model output. Also, 64 and 16 datasets were used for training and testing aims. One of the most important tasks in the PSO-ANFIS modeling is to select the type of membership functions. In the current paper, the Gaussian membership function which has been widely used in many studies, was employed. As suggested by many researchers, the main PSO parameters include maximum number of particles and iterations, initial ( $W_{\min}$ ) and final ( $W_{\max}$ ) inertia weight, Cognitive ( $C_1$ ) and Social ( $C_2$ ) acceleration. To determine the optimum values for the mentioned parameters, trial and error method was performed in this study. Based on the obtained results of trial and error method, the values of 50, 1000, 2, 2, 0.9 and 0.5 for the maximum number of

**Fig. 7** Frequency histogram of the measured powder factor



**Fig. 8** Frequency histogram of the measured Back-break



particles, maximum number of iterations,  $C_1$ ,  $C_2$ ,  $W_{\min}$  and  $W_{\max}$ , respectively, were the best among other utilized values. More discussions regarding the proposed PSO-ANFIS model is given in the Sect. 5.

### 4.2 Prediction of BB using MLR

The MLR is one of the most well-known methods to fit a linear equation between one or more independent variables and one dependent variable. The MLR is widely utilized to predict some problems in the field of mining [46, 47]. For instance, the application of MLR for BB prediction was investigated by Esmaili et al. [9]. Based on their results, the coefficient of determination ( $R^2$ ) between measured and

predicted values of BB by MLR was 0.798 that indicated an acceptable performance for the MLR. Generally, the MLR model can be formulated as follows:

$$Y = P_0 + P_1X_1 + \dots + P_nX_n \tag{8}$$

where,  $X_i (i = 1, \dots, n)$  and  $Y$  denote independent and dependent variables, respectively. In addition,  $P_i (i = 0, 1, \dots, n)$  denote regression coefficients. In the present paper, MLR was developed to predict BB using the same training and testing datasets considering in PSO-ANFIS model. The developed MLR for BB prediction is shown in Eq. 9. It is worth mentioning that the presented Eq. 9 was developed using training datasets. Afterwards, the

**Table 3** Statistical information for the constructed MLR model

Predictor	Coefficient	SE	<i>t</i> Stat	<i>P</i> value
Intercept	0.015	0.17	0.084	0.93
<i>B</i>	0.22	0.06	3.493	0.0008
<i>S</i>	0.16	0.039	4.015	0.0001
ST	0.12	0.037	3.271	0.0016
PF	0.015	0.0009	16.715	5.27E–27

performance of the developed equation can be determined using testing datasets.

$$BB = 0.015 + (0.22 \times B) + (0.16 \times S) + (0.12 \times ST) + (0.015 \times PF), \tag{9}$$

where PF is in terms of gr/cm<sup>3</sup>. Also, *B*, *S* and ST are in terms of *m*. Additionally, Table 3 summarizes statistical information regarding the constructed MLR model. More discussions regarding the developed MLR equation is given in the next section. Note that, MLR was performed using statistical software package, Microsoft Excel 2013.

### 5 Discussion and conclusion

The aim of this study is to predict the BB induced by blasting operations in the Shur river dam region, Iran, using PSO-ANFIS and MLR models. For this aim, 80 blasting events were considered and the values of *B*, *S*, ST and PF, as the most effective parameters on the BB, were measured. In the present paper, 80 and 20 % (64 and 16 datasets) of

the whole datasets were used as training and testing datasets, respectively. In the other words, 64 datasets were used to train/construct the predictive models, while, the remained 16 datasets were used to test the constructed models. In the PSO-ANFIS modeling, the ANFIS is optimized by PSO to improve the performance of ANFIS. In the current study, the optimum values of PSO parameters were determined by trial and error method, as given in Table 4. The Gaussian shaped was also considered as the membership functions. Performance of models established was evaluated using RMSE, coefficient of determination (*R*<sup>2</sup>) and median absolute error (MEDAE).

$$MEDAE = \text{median}(x_i - x_p) \tag{10}$$

$$R^2 = \frac{[\sum_{i=1}^n (x_i - x_{\text{mean}})^2] - [\sum_{i=1}^n (x_i - x_p)^2]}{[\sum_{i=1}^n (x_i - x_{\text{mean}})^2]} \tag{11}$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^n [(x_i - x_p)^2]}, \tag{12}$$

where, *n* denotes number of datasets, *x<sub>p</sub>* and *x<sub>i</sub>* denote the predicted and measured PPV values, respectively. The RMSE, *R*<sup>2</sup> and MEDAE equal to 0, 1 and 1 indicate the best approximation, respectively. The results of statistical indicators for the MLR and PSO-ANFIS models are summarized in Table 5. According to Table 5, When considering the obtained results of the *R*<sup>2</sup> for the MLR model, the values of 0.88 and 0.85 were observed for training and testing datasets, respectively, while, the values of *R*<sup>2</sup> for PSO-ANFIS model were 0.95 and 0.92 for training and testing datasets, respectively. These values demonstrate higher conformity of PSO-ANFIS model. On the other hand, when considering the obtained results of the RMSE for the MLR model, the values of 0.11 and 0.16 were observed for training and testing datasets, respectively, while, the values of RMSE for PSO-ANFIS model were 0.06 and 0.13 for training and testing datasets, respectively. These values reveal a higher accuracy of PSO-ANFIS model. In addition, Figs. 9 and 10 show the scatter plots of BB predicted by the MLR and PSO-ANFIS models for both training and testing data sets. To have a better comparison, the values of predicted and

**Table 4** The optimum values of PSO parameters

Parameter	Value
Maximum number of particles	50
Maximum number of iterations	1000
Initial inertia weight ( <i>W</i> <sub>min</sub> )	0.9
Final inertia weight ( <i>W</i> <sub>max</sub> )	0.5
Cognitive acceleration ( <i>C</i> <sub>1</sub> )	2
Social acceleration ( <i>C</i> <sub>2</sub> )	2

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

Model	Statistical function					
	<i>R</i> <sup>2</sup>		RMSE		MEDAE	
	Train	Test	Train	Test	Train	Test
MLR	0.883	0.857	0.11	0.17	0.1	0.12
PSO-ANFIS	0.958	0.922	0.06	0.13	0.05	0.06



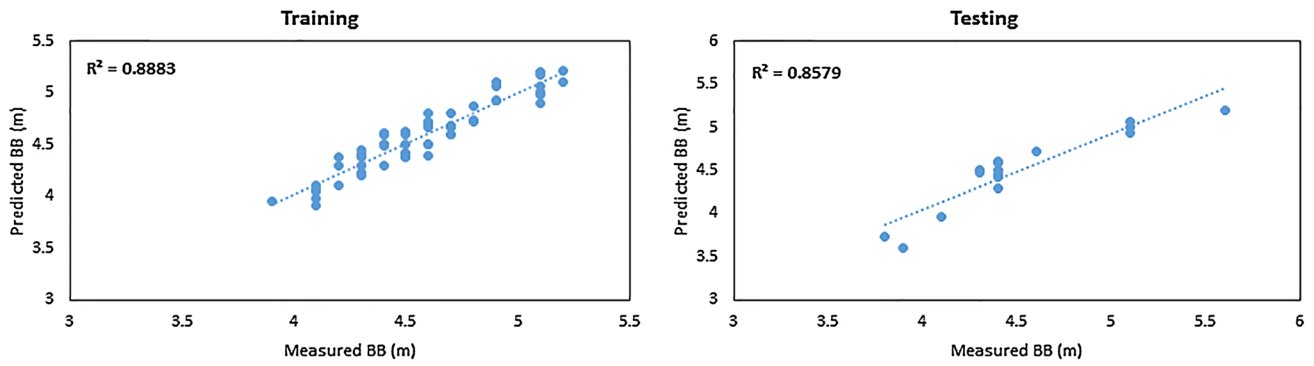


Fig. 9 Comparison of measured BB and predicted BB by MLR model

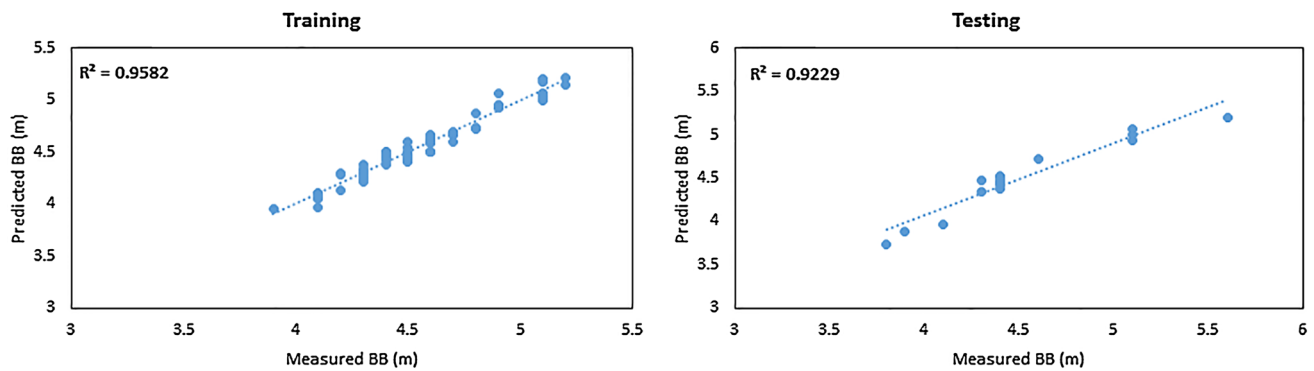


Fig. 10 Comparison of measured BB and predicted BB by PSO-ANFIS model

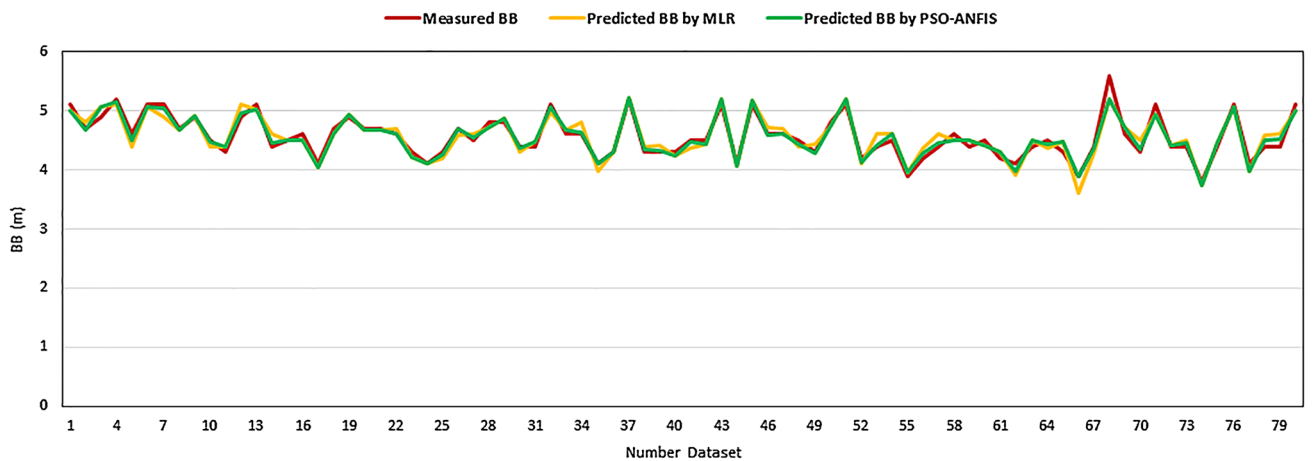


Fig. 11 Comparison of measured BB and predicted BB by MLR and PSO-ANFIS models

measured BB are also plotted for all 80 datasets, as shown in Fig. 11. From Table 5 and Figs. 9, 10, 11, it can be seen that the PSO-ANFIS model predict the blast-induced BB more reliably than MLR model. It is worth mentioning that

developed models in the current paper are specific to Shur river dam. The application of these models directly in other surface mines is not recommended and some modifications are necessary based on blasting and mining conditions.

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