

Combination of neural network and ant colony optimization algorithms for prediction and optimization of flyrock and back-break induced by blasting

Amir Saghatforoush¹ · Masoud Monjezi¹ · Roohollah Shirani Faradonbeh¹ · Danial Jahed Armaghani²

Received: 10 May 2015 / Accepted: 2 September 2015 / Published online: 12 September 2015
© Springer-Verlag London 2015

Abstract Blasting is the process of use of explosives to excavate or remove the rock mass. The main objective of blasting operation is to provide proper rock fragmentation and to avoid undesirable environmental impacts such as ground vibration, flyrock and back-break. Therefore, proper predicting and subsequently optimizing these impacts may reduce damage on facilities and equipment. In this study, an artificial neural network (ANN) was developed to predict flyrock and back-break resulting from blasting. To do this, 97 blasting works in Delkan iron mine, Iran, were investigated and required blasting parameters were collected. The most influential parameters on flyrock and back-break, i.e. burden, spacing, hole length, stemming, and powder factor were considered as model inputs. Results of absolute error (Ea) and root mean square error (RMSE) (0.0137 and 0.063 for Ea and RMSE, respectively) reveal that ANN as a powerful tool can predict flyrock and back-break with high degree of accuracy. In addition, this paper presents a new metaheuristic approximation approach based on the ant colony optimization (ACO) for solving the problem of flyrock and back-break in Delkan iron mine. Considering

changeable parameters of the ACO algorithm, blasting pattern parameters were optimized to minimize results of flyrock and back-break. Eventually, implementing ACO algorithm, reductions of 61 and 58 % were observed in flyrock and back-break results, respectively.

Keywords Blasting · Flyrock · Back-break · Artificial neural network · Ant colony optimization

1 Introduction

Blasting is a common rock fragmentation technique used in mining works, and also several civil engineering applications like tunneling and road construction. Conducting a desired blasting work can cause overall cost reduction, improving the efficiency of drilling operation, increasing cost of loading and cargo, and improving the operation after extraction of minerals [1]. In blasting operation, a large amount of explosive energy are wasted to create environmental impacts like ground vibration, air-overpressure (AOp), flyrock and back-break which can affect surrounding area [2–6].

According to institute of makers of explosives (IME), flyrock is an unexpected throw or movement of the fragmented rock due to excessive force of the explosive material [7]. Flyrock as a serious environmental impact of blasting is often a cause of fatalities, serious injury to people, damage to equipment, building, and property [1]. Based on study conducted by Rustan [8], back-break (BB) is defined as broken rocks beyond the limits of the rear row of holes in a blast pattern. In addition to some risks of BB such as instabilities of equipment and bench, this environmental impact can also cause problems in the next blast-cycle due to escape of gas from the created cracks. According

✉ Masoud Monjezi
monjezi@modares.ac.ir

Amir Saghatforoush
amir.saghatforoush@gmail.com

Roohollah Shirani Faradonbeh
roohollah.Shirani@modares.ac.ir

Danial Jahed Armaghani
danielarmaghani@gmail.com

¹ Faculty of Engineering, Tarbiat Modares University, Tehran 14115-143, Iran

² Young Researchers and Elite Club, Qaemshahr Branch, Islamic Azad University, Qaemshahr, Iran

to many researchers such as Bajpayee et al. [9], Fletcher and D'Andrea [10], Rehak et al. [11], Shea and Clark [12], and Siskind and Kopp [13], generally, mismatch between the explosive material energy and surrounded rock mass strength can cause flyrock. Moreover, Massey and Siu [14] mentioned that loose rocks (with many cracks) in the blast-hole may create flyrock. Gustafsson [15] concluded that energy of flyrock distance has a direct relation with excessive explosive material used in the blast-hole. Furthermore, powder factor and stemming length were selected as the most influential parameter on flyrock in the studies by Monjezi et al. [16] and Rezaei et al. [17], whereas rock density was introduced as the least effective parameter in these studies. In case of back-break, Konya [18] believed that this impact can be increased by increasing the length of burden and stemming. In addition, Gates et al. [19] mentioned two factors as the most influential parameters on BB: inadequate delay time and increasing the number of blast-row. Monjezi and Dehghani [20] reported that stemming to burden ratio, ratio of last row charge to total charge, number of row are the most effective parameters on BB. In another study, Esmaeili et al. [21] concluded that last row charge weight, number of row, powder factor, and stemming length are the most influential parameter on BB, whereas stiffness ratio, burden to spacing ratio and rock density are the least effective parameters.

Empirical models have been utilized for blasting pattern design. Since these models only consider a limited number of effective parameters on blasting environmental impacts, they cannot estimate blasting pattern parameters properly. Previously, several scholars, e.g. Lundborg [22], Roth [23], have been proposed empirical models to predict flyrock and BB. Hustrulid [24] highlighted that proposed empirical methods of flyrock are not good enough in predicting flyrock induced by blasting.

Recently, the use of artificial intelligence (AI) techniques such as artificial neural network (ANN), fuzzy inference system (FIS), adoptive neuro-fuzzy inference system (ANFIS) in solving geotechnical problems is underlined in many studies (e.g. [25–28]). Specially, in the field of blasting environmental impacts, these methods have been widely utilized (e.g. [20, 21]). That is due to the fact that AI-based predictive models take advantage of flexible nature where the models can be easily calibrated when new data become available. This advantage makes them powerful and fast in solving engineering problems more specifically when the problems are highly nonlinear and the contact natures between input and output parameters are unknown [29].

Grima and Babuška [30] and Tonnizam Mohamad et al. [31] proposed an AI model for prediction of uniaxial compressive strength (UCS) of the rock. Alvarez Grima et al. [32] introduced a new model based on ANFIS to predict

tunnel boring machine (TBM) performance. A hybrid ANN-based predictive model was developed to estimate pile bearing capacity in the study carried out by Momeni et al. [25]. Ocak and Seker [33] developed ANN technique for solving problem of surface settlement caused by tunneling. Gordan et al. [34] proposed a hybrid particle swarm optimization (PSO)-ANN to predict seismic stability of the homogeneous slopes. Furthermore, several researchers have been used AI techniques in the case of blasting environmental impacts. Khandelwal and Singh [35] utilized ANN to develop a new model for prediction of ground vibration resulting from blasting. A FIS model was applied and developed by Rezaei et al. [17] to predict flyrock distance. They compared the FIS results with conventional statistical models and showed the higher efficiency of the developed FIS model compared to statistical models. Esmaeili et al. [21] applied ANN, ANFIS and regression models to predict BB using the data of Sangan iron mine, Iran. Their results showed the capability of ANFIS model in predicting BB compared to other used methods. A new approach was developed by Hajihassani et al. [36] based on hybrid particle swarm optimization (PSO) and ANN model for prediction of AOp. The results demonstrated that the presented method is an applicable tool to predict AOp with high degree of accuracy. Table 1 shows recent studies of flyrock and backbreak prediction using AI techniques.

Swarm intelligence is a relatively new approach to solve the optimization problems in which these methods are inspired by the behaviour of insects and animals. Among these, ant colony optimization (ACO) algorithm has been received attention due to its success in optimizing the engineering problems [49]. ACO is a multi-agent optimization algorithm inspired by the behaviour of real ants. It was originally developed to solve discrete optimization problems e.g. travelling sales person [49–51], routing [52, 53] and scheduling [54, 55]. Afterwards, ACO was performed successfully in continuous optimization problems [56]. In the field of mining engineering, only a few studies have been carried out using ACO algorithm. A new metaheuristic approach based on ACO was proposed by Shishvan and Sattarvand [57] for the solution of the problem of open-pit mine production planning. Zhu and Xiao-ping [58] evaluated the indices of human accident at coal mines using ACO algorithm. In another study, Gao [59] developed an abstraction ant colony clustering algorithm for forecasting rockbursts in deep underground engineering. For solving blasting environmental impacts such as flyrock and BB, there is no attempt to optimize blasting parameters using ACO. In the present research, initially, flyrock and BB induced by blasting are predicted by ANN using 97 datasets obtained from Delkan iron mine, Iran. After that, considering the blasting data of Delkan mine and using ACO

Table 1 Recent studies of flyrock and backbreak prediction using AI techniques

References	Technique	Input	Output	No. of dataset	R^2	RMSE
Monjezi and Dehghani [20]	ANN	B, CLR, PF, S/B, ST/B, N	Back-break	300	–	0.64
Monjezi et al. [37]	FIS	B, S, ST, SD, PF, HD, C, RD	Back-break	–	0.95	–
Monjezi et al. [38]	GA-ANN	D, L, B, S, ST, PF, SD, C, RMR	Back-break	195	0.96	–
Monjezi et al. [39]	ANN	UCS, SD, WC, B, S, ST, D, BH, PF, C	Back-break	97	0.9	–
Esmaeili et al. [21]	ANN, ANFIS	SR, ST, PF, RD, N, CLR, S/B	Back-break	42	ANN = 0.92 ANFIS = 0.96	ANN = 0.88 ANFIS = 0.6
Mohammadnejad et al. [40]	SVM	B, S, L, SD, ST, PF	Back-break	193	0.92	0.34
Sayadi et al. [41]	ANN	B, S, L, ST, PF, SD	Back-break	103	0.87	0.22
Monjezi et al. [42]	ANN	B, S, ST, N, PF, DPM, SD, RF	Back-break	–	0.86	0.49
Ebrahimi et al. [43]	ANN	B, S, ST, L, PF	Back-break	34	0.77	0.53
Shirani Faradonbeh et al. [44]	GP	B, S, ST, PF, SR	Back-break	175	0.98	0.32
Monjezi et al. [38]	GA-ANN	D, L, B, S, ST, PF, SD, C, RMR	Flyrock	195	0.98	–
Amini et al. [45]	ANN, ANFIS	L, D, B, S, ST, PF, SD	Flyrock	245	ANN = 0.85 SVM = 0.94	ANN = 7.98 SVM = 4.5
Khandelwal and Monjezi [46]	SVM	L, S, B, ST, PF, SD	Flyrock	234	0.95	–
Jahed Armaghani et al. [47]	ANN-PSO	D, L, C, S, B, ST, PF, RD, J, N	Flyrock	44	0.93	–
Trivedi et al. [48]	ANN	B, PF, ST, UCS, RQD	Flyrock	–	0.98	–

B burden, *S* spacing, *ST* stemming, *PF* powder factor, *C* charge per delay, *N* number of rows, *J* sub drilling, *L* hole depths, *SD* specific drilling, *SR* stiffness ratio, *RD* rock density, *BH* bench height, *RF* rock factor, *WC* water content, *DPM* delay per meter, *Q* linear charge concentration, *CLR* last row charge per total charge ratio, *GP* genetic programming

algorithm, blasting pattern parameters are optimized to minimize the results of flyrock and BB.

2 Method

2.1 Artificial neural network

Artificial neural network (ANN) was developed by McCulloch and Pittsin 1943 [60]. ANNs are composed of large numbers of neurons, while a neuron is a simplification of a biological neuron. Depending on problem to be solved, different numbers of neurons can be utilized. There are various ways to connect the neurons to create an ANN model. Feed-forward (FF)-back-propagation (BP) is the most commonly used ANN type in a wide range of science and engineering as reported by many researchers (e.g. [61–63]). The multi-layer perceptron (MLP) neural network is one of the most well-known FF-ANNs [61, 64]. MLP includes several nodes or neurons in three layers (input, hidden and output) linked to each other by weights. An ANN model with maximum two hidden layers can solve complex engineering problems [20]. Normally, the number of hidden layers and number of neurons in hidden layers are obtained using trial-and-error procedure [65, 66]. In ANN, initially, a desired weight in the range of (0, 1) is assigned to each input parameter. Then, each input is

multiplied by the weight and summation of these amounts is assigned to the hidden layer(s). The obtained value is summed with bias (neuron weight) which is normally equal to one. In the next round, another weight is assigned to the obtained value and the cycle is reached the next layer (output layer). Summation of all obtained values from each layer is the last step of ANN modelling and after that the training procedure is completed and the system is ready to test (or check). In aFF-BP algorithm, the signals flow from input layer to the output layer, called forward pass, then the achieved value(s) from the system is compared to the actual one and the error is computed by the network. The obtained error is propagated back through the network to update the individual weights, called backward pass. In the mentioned process, errors of both training and testing datasets are decreased. FF-BP procedure is repeated until the error is converged to a level defined by a cost function such as root mean squared error (RMSE) [67–69]. However, a database comprising sufficient number of datasets is needed to construct a suitable ANN model.

2.2 Ant colony optimization algorithm

Ant colony optimization (ACO) which was developed by Dorigo [70] is used to solve optimization problems such as the travelling sales person (TSP) as a multi-agent solution. This algorithm is based on studies of the behaviour of real

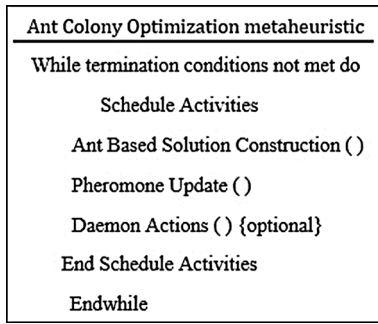


Fig. 1 ACO metaheuristic algorithm [72]

ants that are searching for food source. In this optimization algorithm, a series of artificial ants cooperate to find good solutions using indirect exchange of information via artificial pheromone. The idea behind ACO is the parallel search over numerous computational threads based on local problem data. This search is based on the quality of achieved results which are constructed over time and also a dynamic memory structure of the problem characteristics [71]. In ACO, pheromone is normally associated with the solution components utilized by artificial ants to build new solutions, guiding their decisions. This artificial pheromone is accumulated at run time through a learning mechanism that rewards good solutions. More pheromone on a path increases the probability of that path being followed. An evaporation rule will be tied with the pheromones, which will reduce the chance for poor quality solutions. The superiority of the ACO algorithm compared to other algorithms is mainly based on the appropriateness of solutions generated by colonies. The ACO metaheuristic algorithm is shown in Fig. 1.

Assuming $q_0 \in (0, 1]$, a path that has the greatest amount of pheromones and the minimum distance is selected with possibility of q_0 . Eq. (1) presents a path with possibility of $1 - q_0$:

$$P_{ij}^k = \begin{cases} \frac{(\tau_{ij})^\alpha (\eta_{ij})^\beta}{\sum_{m \in N_i^k} (\tau_{im})^\alpha (\eta_{im})^\beta} & j \in N_i^k \\ 0 & j \notin N_i^k \end{cases} \quad (1)$$

where τ_{ij} is the pheromone value associated with component, η_{ij} is a value that is given by the weighting function (heuristic information), and α and β are positive factors that are used for assigning weight to pheromone and heuristic information, respectively. If $\alpha = 0$, the probability of selecting the closer cities is higher. In fact, in this condition ACO is converted to a stochastic search algorithm. In contrast, if $\beta = 0$, only the pheromone information is utilized. In this case, there will be a faster convergence of the algorithm. If after a while all ants will be converge in a

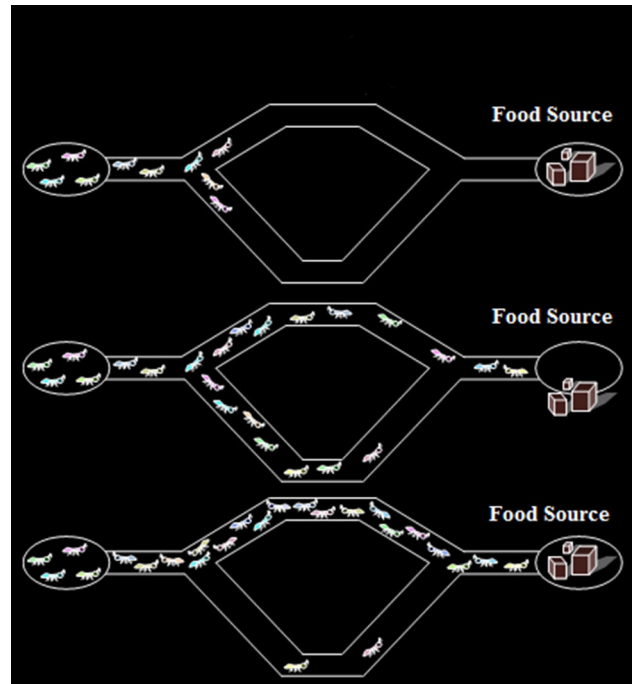


Fig. 2 Cooperation to find the food sources by ants

direction that is generally inappropriate, in this condition, it is said that the algorithm is getting trapped in local minima. Therefore, appropriate balance between pheromone and heuristic information using α and β parameters is very important in ACO algorithm. There are two pheromone updates in ACO algorithm. (1) In the first update which is local, ant colonies distribute pheromones in their path as it can be presented as follows:

$$\tau \rightarrow \tau_{ij} + \rho \tau_0 \quad (2)$$

where τ_0 is initial value of the pheromone and ρ is evaporation coefficient. (2) Second pheromone update which is global is applied on the best paths (ψ^+) in each iteration. If $l_{ij} \in \psi^+$ and J^+ is the path distance of the ψ^+ , pheromone of l_{ij} can be changed as follows:

$$\tau \rightarrow (1 - \rho)\tau_{ij} + \frac{\rho}{J^+} \quad (3)$$

If the evaporation operation is removed from the above equation, then the following equation will be obtained as:

$$\tau \rightarrow (1 - \rho)\tau_{ij} + \frac{\rho}{(1 - \rho)J^+} \quad (4)$$

The two-step planning in ACO algorithm is conducted to create a balance between exploration and exploitation of pheromones [73]. Cooperation to find the food sources (solutions) by ants is illustrated in Fig. 2.



Fig. 3 A view of Delkan iron mine

3 Case study

Delkan iron mine is situated 83 km southwest of Kashmar, in Khorasan Razavi province, Iran. This mine is located in Delkan and Kal Asb mountain area. The maximum height in this region is ascertained to Delkan Mount with height of 1283 m. Delkan mountains with a trend towards the southwest are met mountains of Kal Asb and Kamar Kaseh with height of 1485 m. North side of the study area is relatively flat and hollow with average height of 900 m. Also, south part of the study area is composed of salt (salt desert). It should be noted that the estimated reserve of Delkan iron mine is more than 1 Mt.

A total number of 97 blasting works were investigated and their blasting parameters were measured. In these operations, several blasting parameters including burden, spacing, stemming length, hole length, and powder factor were recorded. The range of powder factor in these operations was observed from 200 to 250 gr/ton. In the established datasets, the maximum and maximum measured stemming lengths were 1.5 and 2 m, respectively. Overall, the design of holes was rhomb-like with distances ($B \times S$) of 2×3 m in the rockdeposit. Moreover, blast-hole length ranging from 8 to 10 m was measured in Delkan iron mine. Ammonium nitrate and fuel oil (ANFO) and soft soil were used as the main explosive and stemming, respectively. BB values were recorded in each operation using measuring tape. To measure flyrock distance in Delkan iron mine, bench surfaces were coloured and two video cameras were put in place to monitor the flyrock projections. After each blasting, the relevant videos were reviewed to find the locations of the maximum rock projections. Then, using measuring tape, flyrock values were recorded. A view of Delkan iron mine is displayed in Fig. 3.

4 Prediction and optimization of flyrock and back-break

4.1 ANN models for predicting flyrock and back-break

In simulation works, preparing a sufficient database plays an important role for training the system. Using the available datasets and considering previous investigations, input parameters can be selected according to problems to be solved. Having the proper input parameters and using the required information for training, complex relationships between input and output parameters can be found by the system. However, in practice, determining all influential parameters on blasting is too difficult. The input parameters in this study have been selected based on previous investigations in the field of back-break and flyrock prediction/optimization. For this purpose, based on the studies presented in Table 1 and also collected data from the mine, burden, spacing, hole depth, stemming length, and powder factor were set as model inputs to predict both flyrock and back-break. Input and output parameters with their statistical details (i.e. range, mean and standard deviation) are listed in Table 2. Since a wide range can be seen for the parameters presented in Table 2, normalization of the datasets was employed before ANN modelling. Rafiq et al. [74] mentioned that normalization of the data can improve the network learning speed. Therefore, all datasets were normalized using the following equation:

$$X_{\text{norm}} = (X - X_{\text{min}})/(X_{\text{max}} - X_{\text{min}}) \quad (5)$$

where X is the measured value, X_{norm} is the normalized value of the measured parameter; X_{min} and X_{max} are the minimum and maximum values of the measured parameters

Table 2 Statistical details of input and output parameters used in this study

Category	Parameter	Symbol	Range	Mean	St. deviation
Input	Burden (m)	B	2–3	2.55	0.27
	Spacing (m)	S	2–3	2.60	0.29
	Hole length (m)	L	8–10	9.16	1.15
	Stemming length (m)	ST	1.50–2	1.74	0.15
	Powder factor (gr/ton)	PF	200–250	229	16.50
Output	Flyrock (m)	–	200–300	245.80	31.30
	Back-break (m)	BB	3–5.5	4.25	0.64

in the dataset, respectively. Considering the above equation, datasets were normalized in the range of [0, 1].

The purpose of the ANN training is to determine the values of weights to achieve the best network based on cost or objective function. Since the output value is determined corresponding to the input vector, the best learning can be considered as supervised learning. Among supervised learning algorithms, BP has been received attention in the field of engineering. Normally, the number of hidden neuron is obtained using the trial-and-error procedure as this method was used in several ANN studies (e.g. [25, 28]). If the selected number of hidden neuron is small, the system cannot train properly and if the selected number of hidden neuron is large, over fitting (a network obtaining a large error) will be happened in the ANN modelling. In this study, all datasets were divided randomly to training and testing datasets. The idea behind using some data for testing is to check the performance capacity of the developed model. A range of 20–30 % of whole data was suggested for testing datasets in the study by Nelson and Illingworth [75]. So, in this study, 30 datasets ($\cong 30\%$), were selected randomly for testing the model development, whereas the remaining 67 datasets were used for training the ANN models. Table 3 shows several constructed ANN models

applied in this study together with their structures and performances. To evaluate the ANN model, absolute error (E_a) and RMSE were utilized. Their equations are presented as follows:

$$E_a = |M_B - P_B| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y - y')^2} \quad (7)$$

where y , y' and \bar{y} are the measured, predicted and mean of the y values respectively, N is the total number of data, M_B , P_B are average measured and average predicted values, respectively. As shown in Table 3, model no. 7 with five inputs (burden, spacing, hole length, stemming length, and powder factor), two hidden layer (including 5 neurons in each layer) and two outputs (flyrock and back-break) outperforms the other models. In the selected model, the values of 0.0137 and 0.063 were obtained for E_a and RMSE, respectively. It is also interesting to note that in ANN analysis of this study, the learning rate and momentum coefficient were set as 0.05 and 0.9, respectively. Figure 4 displays the suggested ANN structure for prediction of flyrock and BB in this study.

The graphs of predicted flyrock using the ANN technique against the measured flyrock for training and testing datasets are shown in Figs. 5 and 6, respectively. R^2 values of 0.989 and 0.994 for training and testing datasets, respectively, show that the ANN approach is able to predict flyrock with high degree of accuracy. In addition, Figs. 7 and 8 illustrate the predicted BB values by performing ANN model plotted against the measured flyrock values for training and testing datasets, respectively. Based on these figures, R^2 values of 0.838 and 0.832 were obtained for training and testing datasets, respectively. These results demonstrate capability of the ANN technique to predict BB. Generally, the results reveal that ANN can be introduced as a powerful tool for prediction of flyrock and back-break induced by blasting works.

Table 3 Several ANN models and their performance capacities applied in this study

Model no.	Transfer function	Structure	E_a	RMSE
1	LOGSIG–LOGSIG–PURELIN (L–L–P)	05-05-2002	0.0183	0.1452
2	LOGSIG–LOGSIG–PURELIN (L–L–P)	05-08-2002	0.0198	0.1306
3	LOGSIG–LOGSIG–LOGSIG–PURELIN (L–L–L–P)	5-3-5-2	0.018	0.1441
4	TANSIG–TANSIG–LOGSIG–LOGSIG (T–T–L–L)	5-9-5-2	0.0154	0.1428
5	LOGSIG–LOGSIG–LOGSIG–PURELIN (L–L–L–P)	5-6-5-2	0.0637	0.1816
6	TANSIG–LOGSIG–LOGSIG–LOGSIG (T–L–L–L)	5-15-5-2	0.0163	0.141
7	LOGSIG–LOGSIG–LOGSIG–PURELIN (L–L–L–P)	5-5-5-2	0.0137	0.063
8	TANSIG–TANSIG–LOGSIG–LOGSIG (T–T–L–L)	5-7-5-2	0.0145	0.1446
9	LOGSIG–LOGSIG–LOGSIG–PURELIN (L–L–L–P)	5-2-5-2	0.0222	0.0858
10	LOGSIG–LOGSIG–LOGSIG–PURELIN (L–L–L–P)	5-12-5-2	0.1157	0.0174

Fig. 4 The suggested ANN structure

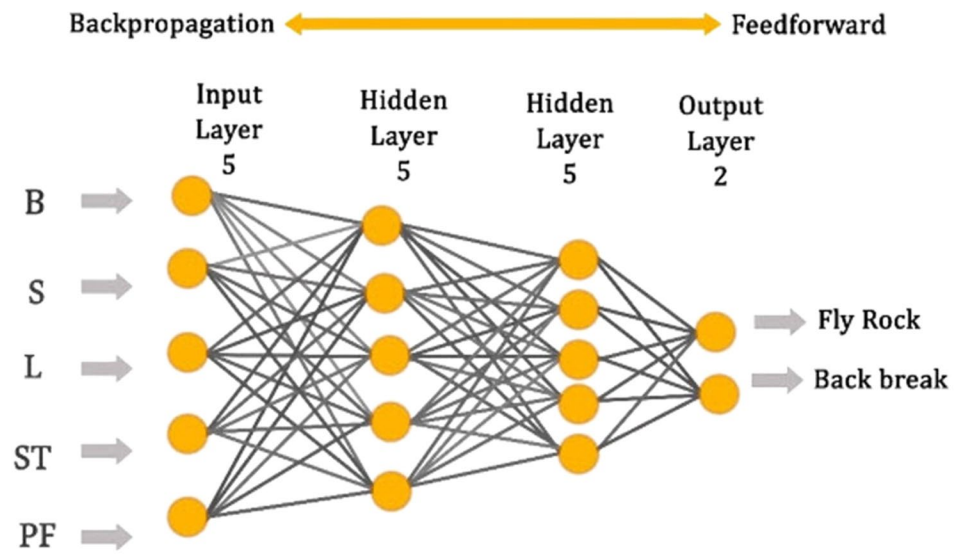


Fig. 5 R^2 of measured and predicted values of flyrock for training datasets using ANN

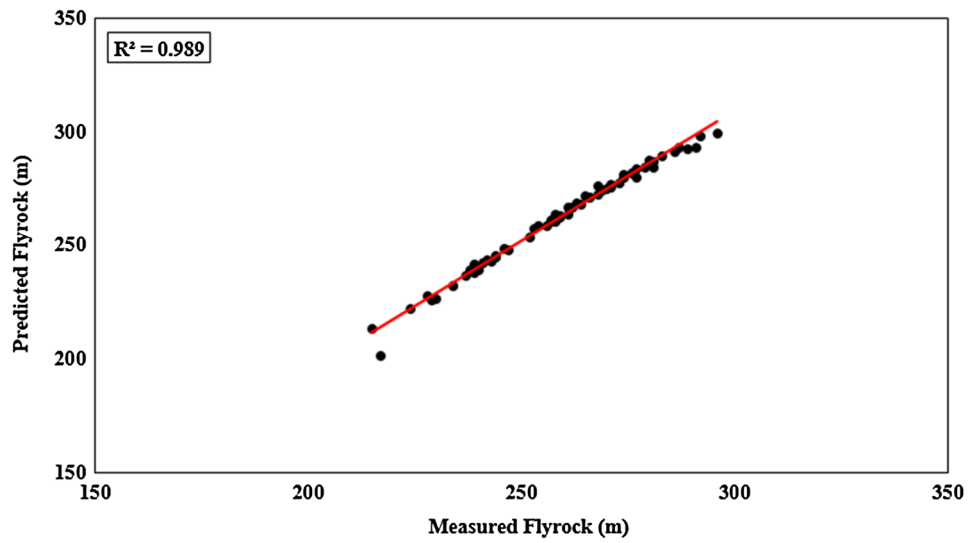


Fig. 6 R^2 of measured and predicted values of flyrock for testing datasets using ANN

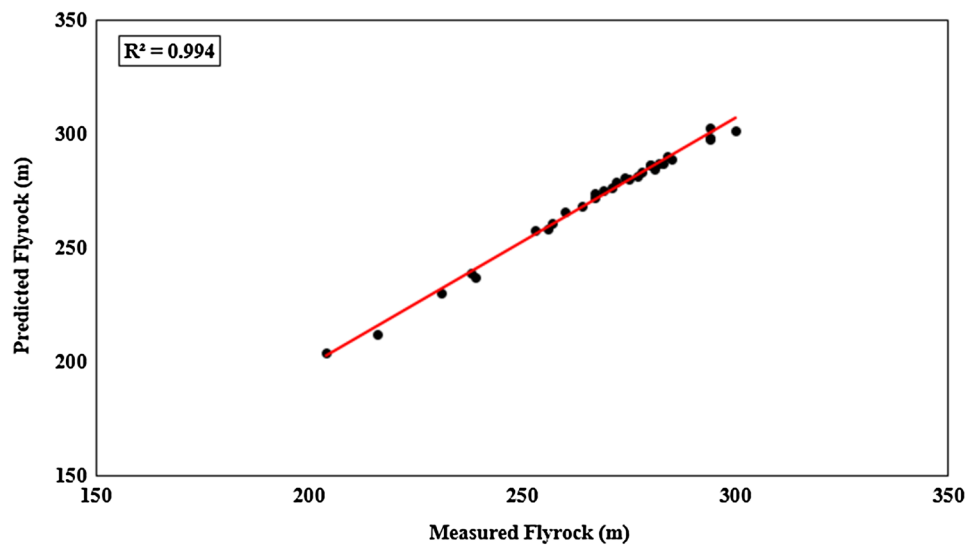


Fig. 7 R^2 of measured and predicted values of back-break for training datasets using ANN

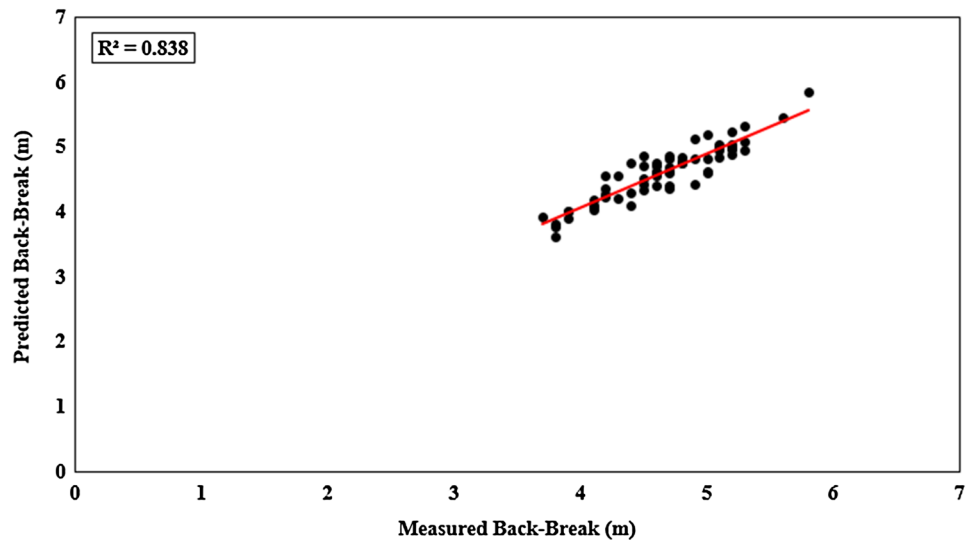
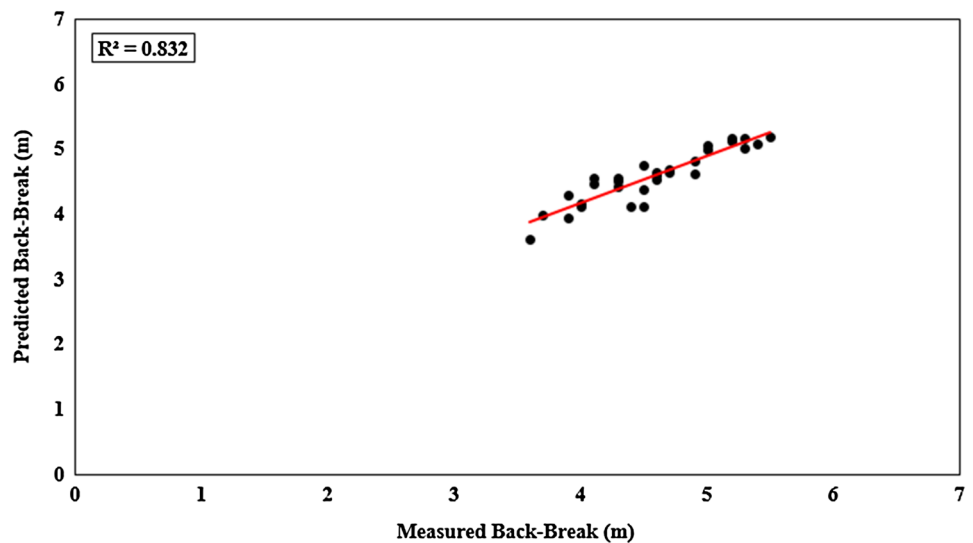


Fig. 8 R^2 of measured and predicted values of back-break for testing datasets using ANN



4.2 Optimization of blasting pattern parameters using ACO algorithm

To optimize the blast pattern parameters for controlling flyrock and BBof Delkan iron mine using ACO algorithm, definition of cost function is required. Hence, the same cost function utilized in the ANN modelling was used. The optimization procedure by ACO used in this research is displayed in Fig. 9. As a first step of the optimization, ANN code is called by ACO algorithm in the MatLab environment and then optimization process is started. The parameters used in ACO algorithm are as follows:

Interval number: Ants are looking for the solutions in the small intervals and find the optimum solution based on the size of the intervals.

Ant number	the number of ants to find the optimal path (tour)
ρ	is a constant which is used for converting the minimum cost function to maximum cost function
Q	is a constant which is used for converting the minimum cost function to maximum cost function
α	is a positive factor that is utilized for assigning weight to pheromone
β	is a positive factor that is used for assigning weight to heuristic information
Iteration	the number of repetition to find the optimum solution
r_0	the values assigned to the various tours

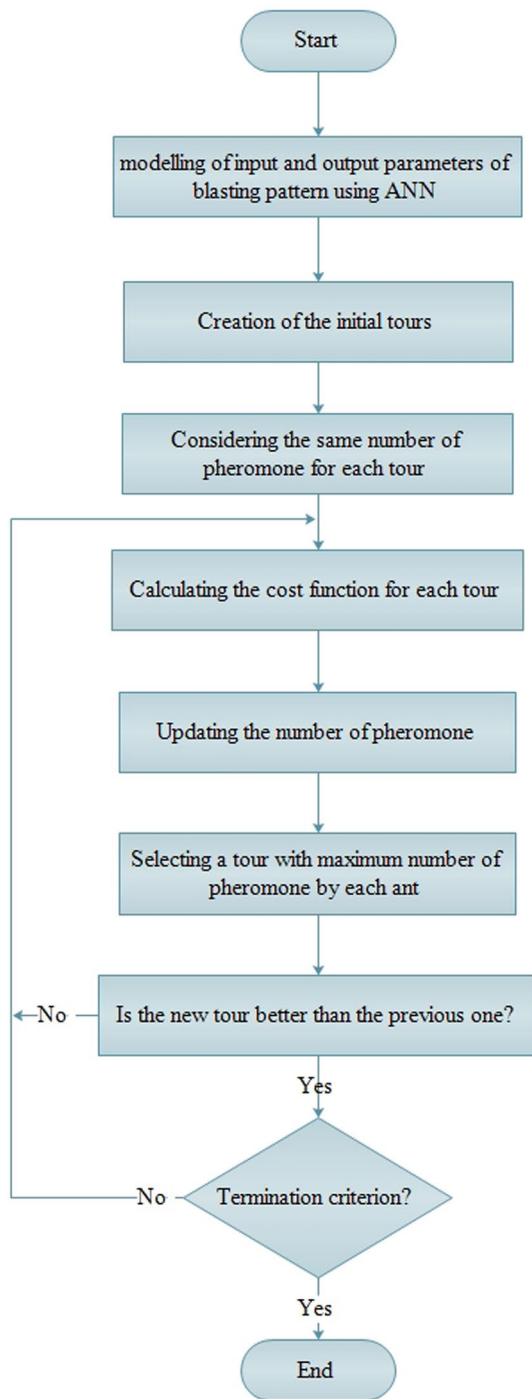


Fig. 9 ACO algorithm

In this study, interval solution was divided by 200 parts, then a tour was selected randomly in these intervals. After that, based on heuristic information, the ants are travelled in the different tours. After a while, ants tend to travel in a particular tour because of pheromones distribution. This particular tour has higher numbers of pheromone compared to other tours. In

this step, using ant tour program, the best intervals are chosen for each input parameter. Since the ants select the shortest tour, hence, the cost function will be minimized. By dividing the cost function on constant value of Q , the cost function can be converted to the maximum function. Finally, after some time, an optimal tour with the best solution from the interval is selected as the best tour. The network is repeated in the remaining tours to find more attractive solutions.

The values of ACO parameters such as α , β , ρ , number of ant and number of iteration were determined using trial-and-error method. Figure 10 shows the analyses' results on the iteration number to find the best solution for optimizing blasting pattern using ACO algorithm. Based on this figure, the significant changes happened in the first iterations, whereas after iteration number 140, there are no changes in network results. Since a lower amount of error was obtained by ants in different iterations, significant changes can be seen in Fig. 10. After the mentioned iteration, there are no significant changes in the results of best cost; therefore, value of 140 was selected for the maximum number of iterations for optimizing blasting pattern parameters. Eventually, a series of values for input parameters were obtained to minimize the results of flyrock and BB of Delkan iron mine. Table 4 presents ACO parameters used in this study for the best optimization results. In addition, Table 5 shows the best parameters of blasting pattern obtained by ACO algorithm. Moreover, optimized values of flyrock and BB can be seen in this table. RMSE values of 0.537 and 0.141 were achieved for flyrock and back-break, respectively. Based on these results, the optimized values of the flyrock and back-break were reduced as 2.5 and 155 m, respectively. Since the blasting operations in the Delkan iron mine are performed close to the location of existing facilities and equipment, by implementing the optimized blasting pattern parameters, these damages will be minimized.

4.3 Model evaluation

To evaluate the ACO algorithm, a function shown in Eq. (8) was utilized. Evaluation of the ACO algorithm is shown in Fig. 11. According to this figure, considering the Eq. (8) in range of $(-3, 3)$, the optimum solution would be very close to zero.

$$Z = X^2 + Y^2 \tag{8}$$

It is worth noting that the minimum value of the mentioned function is $(0, 0)$. The intersection of this function and ACO function is at point of $(0.015, 0.015)$ as it can be seen in Fig. 11. The obtained values of error show capability of the ACO algorithm. This indicates that the ACO algorithm is able to be performed in optimizing blasting pattern parameters.

Fig. 10 The effect of the number of iteration on the ACO network performance

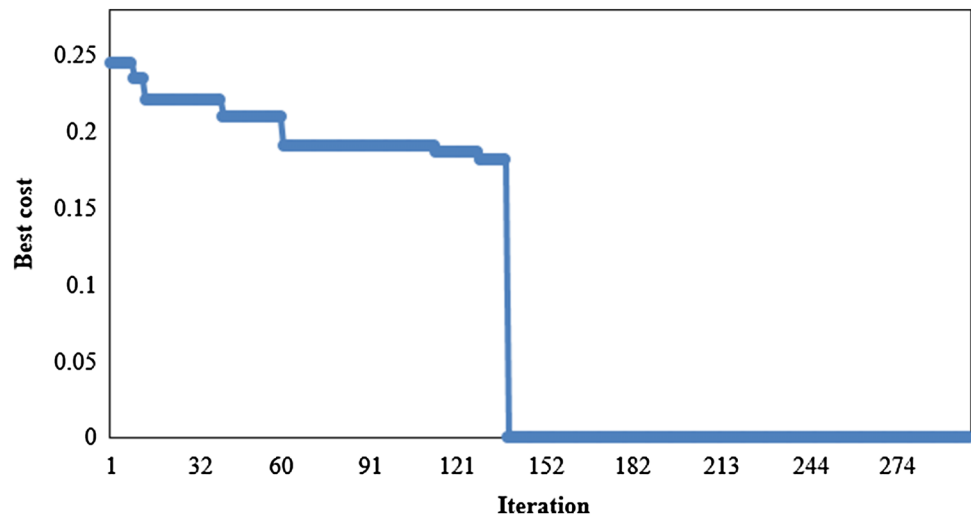


Table 4 ACO parameters used in this study

Controllable parameter	Value
Ant number	30
Interval number	200
Iteration number	300
ρ	0.5
Q	30
α	0.7
β	0.5
r_0	0.4

Table 5 Initial and optimized parameters of blasting pattern using ACO algorithm

Parameter	Unit	Initial value	Optimized value
Burden	m	2.54	2.80
Spacing	m	2.60	3.30
Hole length	m	9.15	10.20
Stemming length	m	1.75	1.50
Powder factor	gr/ton	230	201
Flyrock	m	246	95
Back-break	m	4.25	1.80

5 Conclusion

In this research, an attempt has been made to minimize flyrock distance and back-break induced by blasting operations. To this aim, Delkan iron mine in Iran was investigated and blasting pattern parameters for 97 operations were collected. In addition, flyrock distance and back-break were measured in each operation. Considering the previous investigations and also collected

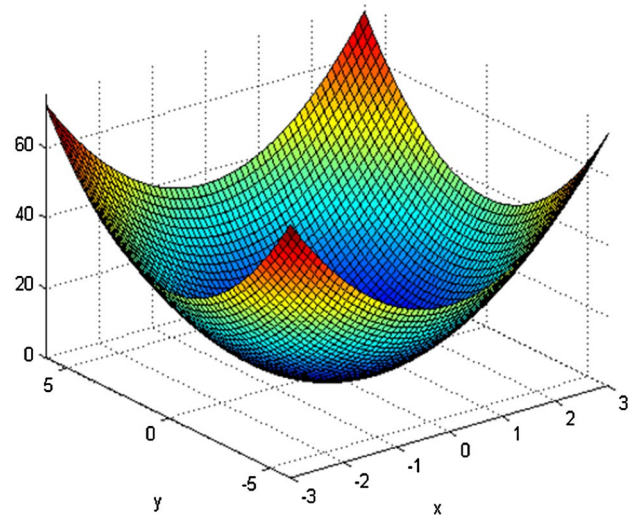


Fig. 11 Evaluating ACO algorithm

data from the mine, burden, spacing, hole length, stemming, and powder factor were selected as input parameters. Initially, using these input parameters, flyrock and back-break were predicted by employing ANN. After trial-and-error procedure, a model with two hidden layers (including 5 neurons in each layer) was chosen as the best ANN model in predicting flyrock and back-break. The R^2 values of 0.994 and 0.832 for testing datasets of flyrock and back-break, respectively, reveal that ANN can provide high performance capacity in predicting flyrock and back-break. Afterward, blasting parameters as well as outputs of ANN part were optimized using ACO algorithm. The values of ACO parameters such as α , β , ρ , number of ant and number of iteration were determined using trial-and-error method. Eventually, reductions of

61 and 58 % were obtained for flyrock and back-break results, respectively. By implementing the optimized blasting pattern parameters, the possible damages caused by flyrock and back-break would be minimized.

References

- Bhandari S (1997) Engineering rock blasting operations. Taylor & Francis, Boca Raton
- Raina AK, Murthy VMSR, Soni AK (2014) Flyrock in bench blasting: a comprehensive review. *Bull Eng Geol Environ*. doi:10.1007/s10064-014-0588-6
- Raina AK, Haldar A, Chakraborty AK, Choudhury PB, Ramulu M, Bandyopadhyay C (2004) Human response to blast-induced vibration and air-overpressure: an Indian scenario. *Bull Eng Geol Environ* 63(3):209–214
- 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*, vol 2014 (Article ID 643715)
- Hajihassani M, Jahed Armaghani D, Monjezi M, Mohamad ET, Marto A (2015) Blast-induced air and ground vibration prediction: a particle swarm optimization-based artificial neural network approach. *Environ Earth Sci*. doi:10.1007/s12665-015-4274-1
- Jahed Armaghani D, Tonnizam Mohamad E, Hajihassani M, Alavi Nezhad Khalil Abad SV, Marto A, Moghaddam MR (2015) Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. *Eng Comput*. doi:10.1007/s00366-015-0402-5
- Institute of Makers of Explosives (IME) (1997) Glossary of commercial explosive industry terms. safety Publication, vol 12. Institute of Makers of Explosives, Washington DC, p 16
- Rustan A (1998) Rock blasting terms and symbols. A.A Balkema, Rotterdam
- Bajpayee TS, Rehak TR, Mowrey GL, Ingram DK (2000) A summary of fatal accidents due to flyrock and lack of blast area security in surface mining, 1989–1999. In: Proceedings of the 27th annual conference on explosives and blasting technique, vol I. International Society of Explosives Engineers, Cleveland
- Fletcher LR, D'Andrea DV (1986) Control of flyrock in blasting. In: Proceedings of the 12th annual conference on explosives and blasting technique. International Society of Explosives Engineers, Cleveland, pp 167–177
- Rehak TR, Bajpayee TS, Mowrey GL, Ingram DK (2001) Flyrock issues in blasting. In: Proceedings of the 27th annual conference on explosives and blasting technique, vol I. International Society of Explosives Engineers, Cleveland, pp 165–175
- Shea CW, Clark D (1998) Avoiding tragedy: lessons to be learned from a flyrock fatality. *Coal Age* 103(2):51–54
- Siskind DE, Kopp JW (1995) Blasting accidents in mines a 16 year summary. In: Proceedings of the 21st annual conference on explosives and blasting technique. International Society of Explosives Engineers, Cleveland, pp 224–239
- Massey JB, Siu KL (2003) Investigation of flyrock incident at Clearwater Bay Road on 6 June. *Civ Eng Dept, Govt Hong Kong Special Admin Region, Hong Kong*, p 49
- Gustafsson R (1973) Swedish blasting technique and mining SPI. Gothenburg, Sweden
- Monjezi M, Amini khoshalan H, Yazdian Varjani A (2011) Optimization of open pit blast parameters using genetic algorithm. *Int J Rock Mech Min Sci* 48:864–869
- Rezaei M, Monjezi M, Yazdian Varjani A (2011) Development of a fuzzy model to predict flyrock in surface mining. *Saf Sci* 49:298–305
- Konya CJ (2003) Rock Blasting and Overbreak Control, 2nd edn. US Department of Transportation, Federal Highway Administration, Washington, DC
- Gates W, Ortiz LT, Florez RM (2005) Analysis of rockfall and blasting backbreak problems. In: Proceedings of the 40th US symposium on rock mechanics. American Rock Mechanics Association, Alexandria, pp 671–80
- Monjezi M, Dehghani H (2008) Evaluation of effect of blasting pattern parameters on flyrock using neural networks. *Int J Rock Mech Min Sci* 45:1446–1453
- Esmaili M, Osanloo M, Rashidinejad F, Aghajani Bazzazi A, Taji M (2012) Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting. *Eng Comput*. doi:10.1007/s00366-012-0298-2
- Lundborg N (1974) The hazards of fly rock in rock blasting. In: Report DS1974, Swedish Detonic Res Found (SveDeFo), Stockholm, p 12
- Roth JA (1979) A model for the determination of flyrock range as a function of shot condition. In: US Bureau of Mines Contract J0387242, Management Science Associates, p 61
- Hustrulid WA (1999) Blasting principles for open pit mining. In: General design concepts, vol 1. AA Balkema, Rotterdam
- Momeni E, Nazir R, Jahed Armaghani D, Maizir H (2014) Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. *Measurement* 57:122–131
- Tonnizam Mohamad E, Jahed Armaghani D, Hajihassani M, Faizi K, Marto A (2013) A simulation approach to predict blasting-induced flyrock and size of thrown rocks. *Electron J Geotech Eng* 18:365–374
- Jahed Armaghani D, Tonnizam Mohamad E, Momeni E, Narayanasamy MS, Mohd Amin MF (2014) An adaptive neuro-fuzzy inference system for predicting unconfined compressive strength and Young's modulus: a study on Main Range granite. *Bull Eng Geol Environ*. doi:10.1007/s10064-014-0687-4
- Ghoraba S, Monjezi M, Talebi N, Moghadam MR, Jahed Armaghani D (2015) Prediction of ground vibration caused by blasting operations through a neural network approach: a case study of Gol-E-Gohar Iron Mine, Iran. *J Zhejiang Univ Sci A*. doi:10.1631/jzus.A1400252
- Garret JH (1994) Where and why artificial neural networks are applicable in civil engineering. *J Comput Civil Eng*. 8:129–130
- Grima MA, Babuška R (1999) Fuzzy model for the prediction of unconfined compressive strength of rock samples. *Int J Rock Mech Min Sci* 36(3):339–349
- Tonnizam Mohamad E, Jahed Armaghani D, Momeni E, Alavi Nezhad Khalil Abad SV (2014) Prediction of the unconfined compressive strength of soft rocks: a PSO-based ANN approach. *Bull Eng Geol Environ*. doi:10.1007/s10064-014-0638-0
- Alvarez Grima M, Bruines PA, Verhoef PNW (2000) Modeling tunnel boring machine performance by neuro-fuzzy methods. *Tunnel Undergr Sp Technol* 15(3):259–269
- Ocak I, Seker SE (2013) Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes. *Environ Earth Sci* 70(3):1263–1276
- Gordan B, Jahed Armaghani D, Hajihassani M, Monjezi M (2015) Prediction of seismic slope stability through combination of particle swarm optimization and neural network. *Eng Comput*. doi:10.1007/s00366-015-0400-7
- Khandelwal M, Singh TN (2006) Prediction of blast induced ground vibrations and frequency in opencast mine—a neural network approach. *J Sound Vib* 289:711–725
- Hajihassani M, Jahed Armaghani D, Sohaei H, Tonnizam Mohamad E, Marto A (2014) Prediction of airblast-overpressure

- induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Appl Acoust* 80:57–67
37. Monjezi M, Bahrami A, Varjani AY (2010) Simultaneous prediction of fragmentation and flyrock in blasting operation using artificial neural networks. *Int J Rock Mech Min Sci* 47(3):476–480
 38. Monjezi M, Khoshalan HA, Varjani AY (2012) Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. *Arab J Geosci* 5(3):441–448
 39. Monjezi M, Bahrami A, Yazdian Varjani A, Sayadi AR (2011) Prediction and controlling of flyrock in blasting operation using artificial neural network. *Arab J Geosci* 4:421–425
 40. Mohammadnejad M, Gholami R, Sereshki F, Jamshidi A (2013) A new methodology to predict backbreak in blasting operation. *Int J Rock Mech Min Sci* 60:75–81
 41. Sayadi A, Monjezi M, Talebi N, Khandelwal M (2013) A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak. *J Rock Mech Geotech Eng* 5(4):318–324
 42. Minjezi M, Ahmadi Z, Yazdian Varjani A, Khandelwal M (2013) Backbreak prediction in the Chadormalu iron mine using artificial neural network. *Neural Comput Appl* 23:1101–1107
 43. Ebrahimi E, Monjezi M, Khalesi MR, Jahed Armaghani D (2015) Prediction and optimization of backbreak and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bull Eng Geol Environ*. doi:10.1007/s10064-015-0720-2
 44. Shirani Faradonbeh R, Monjezi M, Jahed Armaghani D (2015) Genetic programming and non-linear multiple regression techniques to predict backbreak in blasting operation. *Eng Comput*. doi:10.1007/s00366-015-0404-3
 45. Amini H, Gholami R, Monjezi M, Torabi SR, Zadhesh J (2012) Evaluation of flyrock phenomenon due to blasting operation by support vector machine. *Neural Comput Appl* 21(8):2077–2085
 46. Khandelwal M, Monjezi M (2013) Prediction of backbreak in openpitblasting operations using the machine learning method. *RockMech Rock Eng* 46(2):389–396
 47. Jahed Armaghani D, Hajihassani M, Mohamad ET, Marto A, Noorani SA (2014) Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. *Arab J Geosci* 7(12):5383–5396
 48. Trivedi R, Singh TN, Raina A (2014) Prediction of blast-induced flyrock in Indian limestone mines using neural networks. *J Rock MechGeotech Eng* 6(5):447–454
 49. Dorigo M, Maniezzo V, Colomi A (1996) Ant system: optimization by a colony of cooperating agents. *IEEE Trans Syst Man Cybern Part B Cybern* 26(1):29–41
 50. Dorigo M, Gambardella LM (1997) Ant colonies for the traveling salesman problem. *BioSystems* 43(2):73–81
 51. Dorigo M, Gambardella LM (1997) Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Trans Evolut Comput* 1(1):53–66
 52. Bullnheimer B, Hartl RF, Strauss C (1999) Applying the ant system to the vehicle routing problem. In: *Meta-heuristics*. Springer, US, pp 285–296
 53. Mazzeo S, Loiseau I (2004) An ant colony algorithm for the capacitated vehicle routing. *Electron Notes Discrete Math* 18:181–186
 54. Zhang J, Hu X, Tan X, Zhong JH, Huang Q (2006) Implementation of an ant colony optimization technique for job shop scheduling problem. *Trans Inst Measur Control* 28(1):93–108
 55. Dréo J, Siarry P (2004) Continuous interacting ant colony algorithm based on dense heterarchy. *Future Gener Comput Syst* 20(5):841–856
 56. Kong M, Tian P (2006) Application of ACO in continuous domain. In: *Advances in natural computation*. Springer, Berlin, pp 126–135
 57. Shishvan MS, Sattarvand J (2015) Long term production planning of open pit mines by ant colony optimization. *Eur J Oper Res* 240(3):825–836
 58. Zhu J, Xiao-ping M (2009) Safety evaluation of human accidents in coal mine based on ant colony optimization and SVM. *Proced Earth Planet Sci* 1(1):1418–1424
 59. Gao W (2015) Forecasting of rockbursts in deep underground engineering based on abstraction ant colony clustering algorithm. *Nat Hazards* 76(3):1625–1649
 60. McCulloch Warren S, Pitts Walter (1943) A logical calculus of the ideas immanent in nervous activity. *Bull Math Biophys* 5:115–133
 61. Haykin S (1999) *Neural networks*, 2nd edn. Prentice-Hall, Englewood Cliffs
 62. Engelbrecht AP (2007) *Computational intelligence: an introduction*. Wiley, New York
 63. Momeni E, Jahed Armaghani D, Hajihassani M, Amin MFM (2015) Prediction of uniaxial compressive strength of rock samples using hybrid particle swarm optimization-based artificial neural networks. *Measurement* 60:50–63
 64. Jahed Armaghani D, Hajihassani M, Monjezi M, Mohamad ET, Marto A, Moghaddam MR (2015) Application of two intelligent systems in predicting environmental impacts of quarry blasting. *Arab J Geosci*. doi:10.1007/s12517-015-1908-2
 65. Poulton MM (2002) Neural networks as an intelligence amplification tool: a review of applications. *J Geophys* 67(3):979–993
 66. Baheer I (2000) Selection of methodology for modeling hysteresis behavior of soils using neural networks. *J Comput Aided Civil Infrastruct Eng* 5(6):445–463
 67. Demuth H, Beale M (2002) *Neural network toolbox user's guide version 4*. The Math Works, USA
 68. Negnevitsky M (2002) *Artificial intelligence: a guide to intelligent systems*. Addison-Wesley, England
 69. Simpson PK (1990) *Artificial neural system: foundation, paradigms, applications and implementations*. Pergamon, New York
 70. Dorigo M (1992) *Learning and natural algorithms, in electrical engineering*. Politecnico di Milano, Italy
 71. Hajizadeh Y, Christie M, Demyanov V (2011) Ant colony optimization for history matching and uncertainty quantification of reservoir models. *J Pet Sci Eng* 77(1):78–92
 72. Socha K, Dorigo M (2008) Ant colony optimization for continuous domains. *Eur J Oper Res* 185(3):1155–1173
 73. Dorigo M, Gambardella LM (2006) *Ant colony optimization and swarm intelligence*. Springer, Berlin
 74. Rafiq MY, Bugmann G, Easterbrook DJ (2001) Neural network design for engineering applications. *Comput Struct* 79:541–1552
 75. Nelson M, Illingworth WT (1990) *A practical guide to neural nets*. Addison-Wesley, Reading