Engineering with Computers (2019) 35:1191–1202
https://doi.org/10.1007/s00366-018-0658-7

ORIGINAL ARTICLE

Overbreak prediction and optimization in tunnel using neural network and bee colony techniques

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Received: 11 August 2018 / Accepted: 16 October 2018 / Published online: 24 October 2018

Abstract

Overbreak is an undesirable phenomenon in blasting operations. The causing factors of overbreak can be generally divided as blasting and geological parameters. Due to multiplicity of effective parameters and complexity of interactions among these parameters, empirical methods may not be fully appropriated for blasting pattern design. In this research, artificial neural network (ANN) as a powerful tool for solving such complicated problems is developed to predict overbreak induced by blasting operations in the Gardaneh Rokh tunnel, Iran. To develop an ANN model, an established database comprising of 255 datasets has been utilized. A three-layer ANN was found as an optimum model for prediction of overbreak. The coefficient of determination (R^2) and root mean square error (RMSE) values of the selected model were obtained as 0.921, 0.4820, 0.923 and 0.4277 for training and testing, respectively, which demonstrate a high capability of ANN in predicting overbreak. After selecting the best model, the selected model was used for optimization purpose using artificial bee colony (ABC) algorithm as one of the most powerful optimization algorithms. Considering this point that overbreak is one of the main problems in tunneling, reducing its amount causes to have a good tunneling operation. After making several models of optimization and variations in its weights, the optimum amount for the extra drilling was 1.63 m^2, which is 47% lower than the lowest value (3.055 m^2). It can be concluded that ABC algorithm can be introduced as a new optimizing algorithm to minimize overbreak induced by tunneling.

Keywords Tunneling · Overbreak · Artificial neural network · Artificial bee colony · Optimization algorithms

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1 Introduction

The tunnels have been excavated for various purposes such as road construction and water transferring in civil and mining works. Although new mechanized excavation methods such as tunnel boring machine (TBM) have been successfully utilized for tunnel excavation, drilling and blasting as a traditional technique can be still used for excavation of tunnels with different shapes and sizes [1]. In fact, it is a primary excavation technique due to its advantages of high flexibility and low cost [2]. Nevertheless, because of using explosive material for rock mass excavation, damages to the peripheral rock mass around the excavation are inevitable. After the blast operation, the excavation cross-section can have two major problems. These two problems (Fig. 1) are called overbreak and underbreak. The over break is defined as a surplus drilled section of the tunnel and the underbreak is defined as the remainder of the blast operation.

Overbreak phenomenon in the executive process of a tunneling project is always one of the most important issues. Nowadays, according to the progress of industry and entrance of new technologies to tunneling industry and gradual acceptance, the new methods are replaced instead of traditional methods (drilling and blast). Though, the tunneling industry uses advanced equipment, there are still reports of the overbreak phenomenon. The main reason is referred to the variety of gender stone and various geological effects which generally cannot be predicted until approaching time. On the other hand, tunnel projects with low volumes, small to medium scale, employers and contractors are unwilling to invest for entering the new mechanized equipment instead of traditional methods. Therefore, it can be argued that the traditional methods specially drilling and blasting are the most common tunnel excavation method for small-to-medium-scale projects. It should be noted that, as far as writers are concerned, there is no experimental and analytical method on the determination of overbreak in the tunnels.

Recently, artificial intelligence (AI) methods such as artificial neural networks (ANN), fuzzy inference system (FIS),

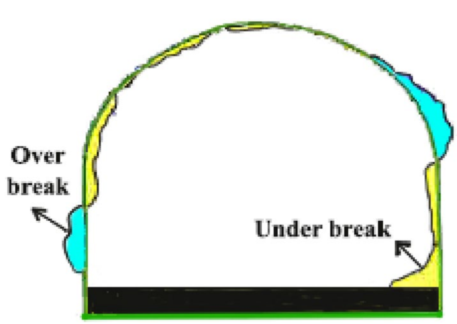

Fig. 1 A schematic photo of overbreak and underbreak in tunnels

and neuro-fuzzy inference system (ANFIS) are developed to solve geotechnical problems [3–18]. Several researchers used AI methods to predict the uniaxial compressive strength of the rock [19–22]. Momeni et al. [23] highlighted the use of ANN technique to predict bearing capacity of the pile. In addition, this method was utilized to solve the problem of ground settlement induced by tunneling in the study carried out by Ocak and Seker [24]. Gordan et al. [25] predicted the stability of homogeneous slopes using a combination of particle swarm optimization (PSO) and ANN.

The effective factors of overbreak can be divided into three groups of rock mass characteristics, geometric properties of the explosion pattern and blasting properties [26]. So far, many researches worked on overbreak in mines and tunnels. Monjezi and Dehghani [27] considered the ratio of stemming to burden, charge the last row to total charge, special charge, special charge per delay and the number of explosion rows in each stage in the GOL-GOHAR mine, Iran as the most influencing factors on overbreak. Hyongdoo Jang and Erkan Topal [28] predicted the overbreak of the Gyby tunnel in South Korea with a value of 0.945 for correlation coefficient (R) between the output of model and the actual data, using ANNs. Their model inputs include uniaxial compressive strength of the rock mass, quality index of rock mass, rock weathering conditions, groundwater conditions, and geomechanical classification index values of rock mass to predict over break.

To propose a comprehensive ANN model, Monjezi et al. [29] used parameters of uniaxial compressive strength, especially drilling, underground water content, burden, hole spacing, stemming, the diameter of the hole, stair height, special charge and consumer charge in ever delay as model inputs. They surveyed the sensitivity analysis on the mentioned parameters and concluded that burden and underground water content are the most effective and least important parameters, respectively. Hook and Brown [30] reported that when discontinuities are parallel along the tunnel axis, they have undesirable effects on over break. Ebrahimi et al. [31] introduced burden, spacing and charge per delay as the most influential parameters on overbreak. Developing an ant colony optimization algorithm, Saghatforoush et al. [32] reduced overbreak and flyrock resulting from blasting, 61 and 58%, respectively.

Gates et al. [33] expressed that insufficient delay time and the number of explosive rows are the most effective factors on over break. Esmaeili et al. [34] suggested that the last row of charge and special charge are the most important factors on over break, while the ratio of burden to spacing, stiffness and density are the least important ones. Ibarra et al. [35] mentioned that the charge factor of environment from explosive can create underbreak in tunnels and the reduction of rock quality may create over break. Mandal [26] expressed that in addition to the rock conditions, in situ stress has also a deep effect on overbreak. Several researchers have suggested empirical models to estimate overbreak [36, 37]. Singh and Xavier [38] carried out a series of small experiments on the physical-scale models to predict the blast damage. They considered characteristics of the rock mass and the explosive material as the most effective parameters on overbreak. Recently, Koopialipoor et al. [39] used a hybrid of genetic algorithm (GA)-ANN model for prediction of overbreak in tunnels and successfully demonstrated that their developed models can predict overbreak with high degree of accuracy.

By reviewing mentioned works, it can be concluded that due to the multiplicity of the effective factors as well as the complex relationship between these parameters, there is a need to develop a new technique to predict and control overbreak phenomenon. On the other hand, parameters influencing overbreak are related to the specific condition of the project. Therefore, it is necessary to evaluate overbreak phenomenon for each project before conducting the operations. The present study attempts to predict overbreak phenomenon at Gardaneh Rokh tunnel, Iran, using ANN approach. Then, artificial bee colony (ABC) is considered and proposed to optimize the blast pattern parameters for minimization of overbreak in the tunnel.

This paper is presented in seven sections: after the current section, the studied location together with data collection will be explained in Sect. 2. Sections 3 and 4 are about background of ANN model and how to implement it for prediction of over-break, respectively. Some material regarding structure of ABC can be found in Sect. 5 and in Sect. 6, modelling process of ABC and its effective parameters to optimize over-break will be described. Finally, the conclusions of this paper are given in the last section.

2 Case study

The Gardaneh Rokh tunnel is one of the most important tunnels in West of Iran. The tunnel is the main road of communication between two centers of Esfahan, and Chaharmahal and Bakhtiari provinces. The road to Isfahan–Shahrekord is economically and strategically crucial highways in Iran. The mentioned tunnel which is a communication path was removed to 7 km from the capital of the provinces and about 100 twists and accident-prone points on this axis. The tunnel with a length of 1300 m and width of 13 m was investigated in Chaharmahal and Bakhtiari Province which is located at a distance of 30 km from Shahrekord city. The location of the study area can be seen in Fig. 2. Excavation of this tunnel, as shown in Fig. 3, was performed in two sections: the top one which was excavated using drilling and blasting method, and the bottom one which was excavated using hydraulic hammer.

In excavation operations of top section, the relatively constant explosive pattern was used to drill the tunnel. In this project, there are some minor changes in the pattern of explosions, but the changes were not varied enough to be considered in different arrangements for each stage of the explosion. Table 1 shows general specifications of excavation at top section of the tunnel with a period of explosive design parameter changes in different conditions of rock mass.

In this study, eight parameters were selected as inputs of model for prediction of overbreak, which included 255 datasets of RMR, advanced length, special charge, the holes periphery burden, the end row burden, periphery spacing, end row spacing, and number of applied delay. A simple description of these parameters (input and output) is shown in Table 2.

3 Artificial neural network

Artificial neural network (ANN) was developed by McCulloch and Pittsin [40]. This flexible technique is a type of artificial intelligent (AI) sytem which can solve problems faster with a high degree of accuracy. Furthermore, it can be used to solve non-linear nature issues where input and output parameters are considered as unknown [41]. The ANN is an imitation of the mechanism of data analysis of biological cells. The brain is a high complex network which can act as a parallel processor. Such networks are designed mainly for a series of non-linear mapping between input and outputs. ANNs are learned from previous experiences and generalized using the training samples. They are able to change their behavior based on the environment and are appropriate for the required algorithms for mapping. In ANN systems, the data used to create models are known as training data. In other words, ANNs use training data to learn patterns in the data which can prepare them to achieve the different outputs and results [42]. The structure of ANNs is created by processor units (neurons or nodes), which are responsible for the organization. These neurons can be combined with each other to form the layer. There are different ways to link neural in ANN. Feedforward (FF)-back-propagation (BP) is a common procedure for application in ANNs that its successful use has been reported by many researchers [14, 23, 43–46]. Each neuron has multiple inputs. These inputs are combined and then the combination of them provides an output after processing. Network cells are connected to each other which output of each cell is considered as the next cell input. The first layer on the left side of the input layer does not play any role in processing and, inputs only import in this section, through existing communications sent to the next layer to the process. The end layer (layer right) is an output layer that provides network response. The layers

Fig. 2 The location of the study area

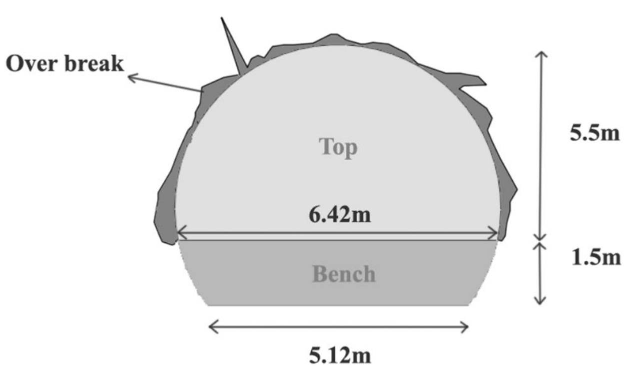

Fig. 3 Cross-section of the studied tunnel

between input and output layer are called hidden or intermediate layers [47].

One of the most widely learning algorithms in ANN is learning algorithm of error back propagation [48]. The algorithm works on the basis of the error correction learning law, which can be considered extended algorithm of at least average. In general, learning propagation consists of two steps: forward step and back step. In forward stage, the inputs are forward layer by layer in the network, and finally a series of network output will be obtained as predicted values. During the forward stage, synaptic weights will be achieved. On the other hand, in the backward process, the weights are set the error by regulating laws. The difference between predicted response and network response (expected), which is called the error signal, will be released in the opposite

Table 1 General specifications of excavation at top section of the tunnel using drilling and blasting

Features	Description
Shape	Horseshoe
The cross-section of the top	32.15 (m^2)
The tunnel periphery at top section	15.052 (m)
Hole diameters	45 and 51 (mm)
The type of consumption explosive	Gelatin dynamite
Number of holes	45–85
Consumption detonator	Delay 0.5 s—with different numbers
Hole depth	1.2–3 (m)
Arrangement of holes in the cutting area	Wedge shape
Cut the hole angle relative to a line perpendicular to the axis of the tunnel	69–72 (°)
The total weight of consumption explosives	48–118 (kg)
Charge of holes	Continuous
Stemming length	According to the conditions stone from 15 to 60 cm

Table 2 Statistical description of input and output data

Standard deviation	Minimum	Maximum	Symbol	Unit	Parameters
1.2	4	10	ND	–	Number of delay
0.2	0.6	2	B_1	m	Periphery burden
0.22	0.6	1.8	B_2	m	End row burden
0.17	0.3	1.7	S_1	m	Periphery spacing
0.17	0.6	1.25	S_2	m	End row spacing
0.23	0.49	1.65	Q	kg/m^3	Special charge
0.58	0.9	3.96	AL	m	Advanced length
6.47	30	39	RMR	-	Rock mass rating
2.47	3.05	8.37	OB	m^2	Overbreak

Table 3 Existing relationships to determine hidden layer neurons

References	Relationships
[56]	$\leq 2\times N_i + 1$
[57]	$(N_i + N_0)/2$
[58]	$\frac{2+N_0\times N_i+0.5N_0\times(N_0^2+N_i)-3}{N_i+N_0}$
[59]	$2N_i/3$
[60]	$\sqrt{N_i \times N_0}$
[61, 62]	$2N_i$

direction of network connections and the weights change in a way that predicted response becomes closer to favorable response. Since the recent distribution is made in contrast to the weighted connections, error back propagation is chosen to explain the modification behavior of network. Different performance indices can be used to evaluate system results [42, 49–54]:

A. The correlation coefficient (R^2)
B. The root mean square error (RMSE)

4 Developing ANN model

In the current study, the perceptron ANN model, which consists of three layers, was used to predict overbreak. Herein, three different learning algorithms were used to learn the ANN. These three algorithms include Levenberg–Markvart (LM), one-step secant (OSS) and scaled conjugate gradient (SCG), which can be compared between common functions for choosing the best learning function. Some researchers have proven that three layers can solve various and nonlinear issues (e.g., Hornik et al. [55]). For this, the number of neurons in the first layer is equal to the number of input data (nine neurons). In addition, since the goal is an outlet, a neuron is also determined in the output layer. Finally, for determining hidden layer, several research studies have been conducted to select the number of hidden layer neurons in which they suggested appropriate numbers. There is a need to conduct trial and error methods to obtain the appropriate values for hidden neuron number. In Table 3, several researchers have proposed relationships to select the number of neurons in which N_i is the number of inputs, no is the number of outputs of the model.

According to the values of relationships presented in Table 3, for all three neural network learning algorithms from a range between 2 and 18 neurons for hidden neuron number was considered. Considering the importance of R^2 and RMSE of each series of training and testing systems, a comparison was made between them to select the best model. This comparison is based on a proposed technique by Zorlu et al. [63], where each section is evaluated assigning a score. Based on this method, every performance index (R^2 or RMSE) was calculated in its own class and best of them got highest ratin/ranking. For instance, values of 0.913, 0.913, 0.904, 0.908, 0.902, 0.912, 0.912, 0.913, 0.913, 0.902, 0.898, 0.931, 0.925, and 0.915 were obtained for section of R^2 training dataset for models 1–14, respectively. Ranking results of the mentioned 12 models were, respectively,

Table 4 Prediction values of overbreak using ANN model

Learning function	No. model	No. neuron	Train		Test		Train rating		Test rating		Total rank
			R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
SCG	1	2	0.913	0.411	0.919	0.3787	31	14	38	42	125
	2	3	0.913	0.409	0.902	0.4144	31	16	30	32	109
	3	4	0.904	0.416	0.923	0.3881	27	13	40	38	118
	4	5	0.908	0.42	0.937	0.3818	28	11	41	40	120
	5	6	0.902	0.424	0.921	0.4263	26	9	39	26	100
	6	7	0.912	0.394	0.908	0.464	30	27	33	13	103
	7	8	0.912	0.403	0.912	0.4277	30	23	35	25	113
	8	9	0.913	0.404	0.893	0.4722	31	22	28	10	91
	9	10	0.913	0.391	0.906	0.4582	31	29	32	17	109
	10	11	0.902	0.431	0.91	0.4188	26	7	34	30	97
	11	12	0.898	0.431	0.885	0.4835	25	7	23	8	63
	12	14	0.931	0.363	0.87	0.4795	40	41	21	9	111
	13	16	0.925	0.364	0.891	0.5474	37	40	26	2	105
	14	18	0.915	0.391	0.885	0.5	32	30	23	5	90
LM	15	2	0.923	0.38	0.906	0.4494	36	36	32	19	123
	16	3	0.917	0.4	0.902	0.4511	33	25	30	18	106
	17	4	0.923	0.384	0.902	0.4716	36	31	30	11	108
	18	5	0.913	0.406	0.912	0.3896	31	19	35	37	122
	19	6	0.913	0.378	0.904	0.4131	31	37	31	33	132
	20	7	0.919	0.382	0.913	0.4477	34	34	36	20	124
	21	8	0.921	0.372	0.923	0.4308	35	39	40	24	138
	22	9	0.919	0.411	0.896	0.4955	34	15	29	6	84
	23	10	0.904	0.42	0.921	0.4187	27	12	39	31	109
	24	11	0.929	0.38	0.883	0.4896	39	35	22	7	103
	25	12	0.904	0.545	0.887	0.4429	27	3	25	21	76
	26	14	0.927	0.384	0.886	0.5517	38	33	24	1	96
	27	16	0.935	0.407	0.866	0.5428	41	17	19	3	80
	28	18	0.944	0.33	0.868	0.5018	42	42	20	4	108
OSS	29	2	0.891	0.438	0.912	0.4618	24	5	35	15	79
	30	3	0.902	0.439	0.913	0.433	26	4	36	23	89
	31	4	0.91	0.426	0.908	0.3834	29	8	33	39	109
	32	5	0.902	0.421	0.938	0.3715	26	10	42	41	119
	33	6	0.915	0.393	0.917	0.4395	32	28	37	22	119
	34	7	0.917	0.404	0.904	0.3947	33	21	31	36	121
	35	8	0.912	0.405	0.913	0.4257	30	20	36	27	113
	36	9	0.921	0.384	0.912	0.4225	35	32	35	29	131
	37	10	0.91	0.407	0.904	0.4242	29	18	31	28	106
	38	11	0.929	0.372	0.893	0.4644	39	38	27	12	116
	39	12	0.921	0.391	0.893	0.4604	35	30	27	16	108
	40	14	0.898	0.436	0.923	0.4063	25	6	40	35	106
	41	16	0.913	0.394	0.91	0.4638	31	26	34	14	105
	42	18	0.912	0.402	0.913	0.409	30	24	36	34	124

obtained as 31, 31, 27, 28, 26, 30, 30, 31, 31, 26, 25, 40, 37, and 32. It should be noted that scores are generated for 42 models, the highest score of which is assigned to the best section, and if the two sections are the same, the same score is awarded to them. Finally, the score of each row is aggregated from the models and is considered as a total score. Table 4 presents the results of this neural network. As shown in Table 4, Model No. 21 created with the LM learning algorithm was selected as the best model based on the highest score.

Figures 4 and 5 show the results of training and testing stages for the selected model (model number 21). As it can be seen, R^2 values of 0.921 and 0.923 for training and testing show ability of ANN model in predicting overbreak. In fact, ANN can provide a high-level prediction capacity for the estimation of overbreak with a low error.

In the following, basis of an optimization algorithm, namely, artificial bee colony (ABC), in optimizing overbreak and its effective parameters are described. After that, minimization process of overbreak and input parameters will be presented and discussed.

5 Artificial bee colony

In this research, one of the new optimization algorithms called ABC algorithm has been used. This algorithm is based on the life of bees and is introduced by Karaboga

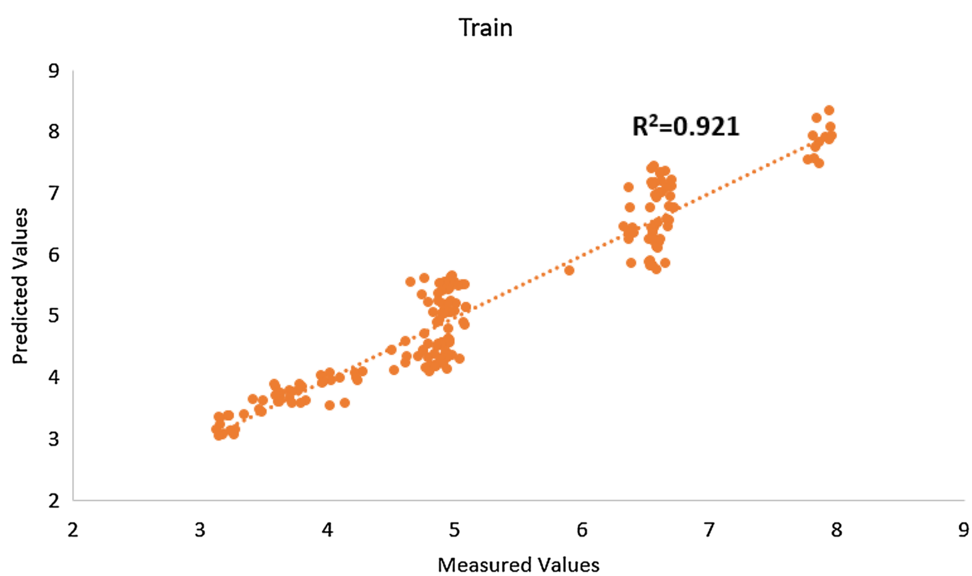

Fig. 4 Prediction values of overbreak for train model No. 21

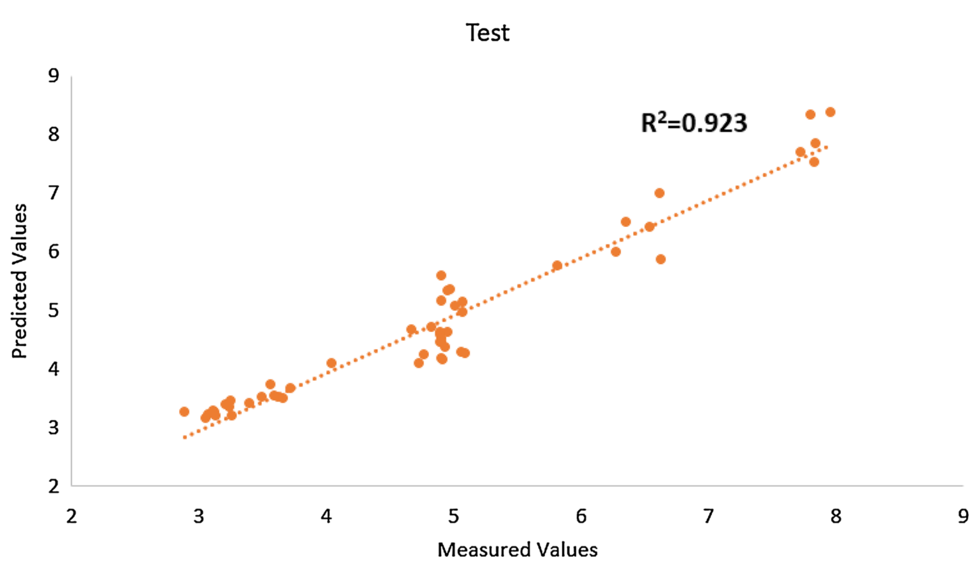

Fig. 5 Prediction values of overbreak for test model No. 21

[64]. In this algorithm, the bees form a colony together. In Clooney, the bees are just as simple components of the whole collection, which can be used to explore and search resources (answers). The same thing causes use of this algorithm to find the answers of the various problems. There are three major groups in each colony that work together to look for the best answer. The first group, known as scout bees, is used in the environment (search space) to seek resources (goals or problem answers). After returning the bees to the hive and exchanging information with the second-group bees (employed bees), the discovered resources begin to extract. Finally, the third group of bees (onlooker bees) in the hive uses resource information to evaluate responses in terms of fitness and provide the best sources (answers) to the hive (system). In this research, algorithm coding is implemented in MATLAB environmental software. The general flowchart of this algorithm, which is used to optimize overbreak in tunnels, is presented in detail in Fig. 6.

Recently, this algorithm has been applied in various engineering fields [31, 65–69]. Its major applications are to optimize engineering issues. Furthermore, some researchers have recently used this algorithm to improve the performance of ANN [3, 44]. More details regarding ABC structure and how to work, can be found in other studies [64, 70, 71].

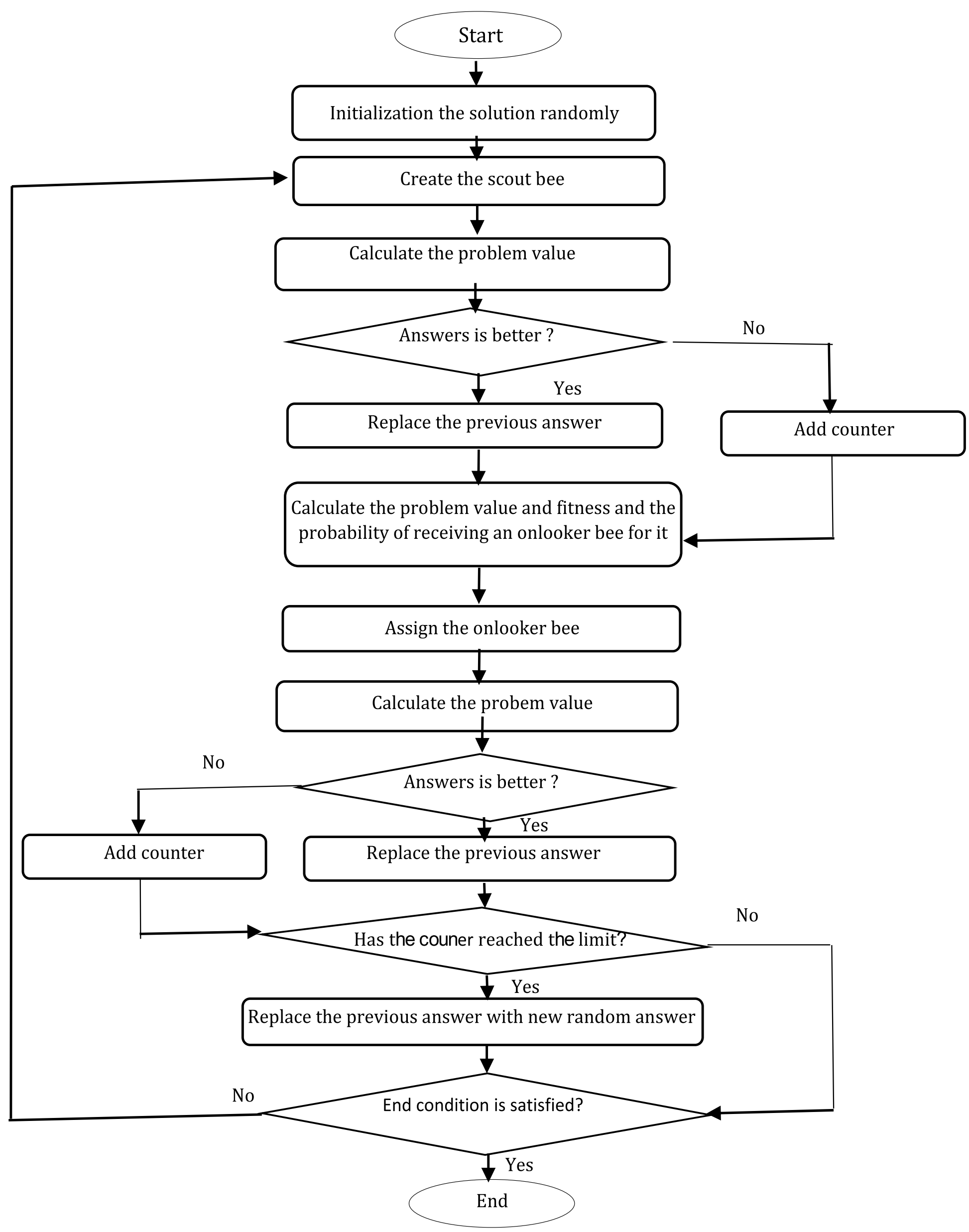

Fig. 6 Structure of ABC algorithm to optimize the overbreak in tunnels

6 Optimization of overbreak by ABC

In this research, after selecting the best ANN network (No. 21), the ABC algorithm was used to minimize overbreak results of the tunnel. Considering the amount of RMR which is varies from 30 to 39, the highest number of samples was selected with a RMR of about 36, and an optimization for this range was obtained from the rock mass of the tunnel pathway. As the complete explanation of this algorithm is given above, this search continues to find the minimum amount of over break. Several models of the ABC algorithm were implemented with different bees. In Fig. 7, several results of the algorithm show the best cost of over break.

As shown in Fig. 7, the bee impacts were evaluated considering total iteration number of 300 and number of bees in the range of 15–60. As a result, generally, system performance would be better by increasing number of bees. Nevertheless, after number of bees = 40 there was a very small difference between results of system. Hence, 40 was selected as the appreciate bee number. Focusing on iteration number, it was also found that after iteration number = 150, there was almost no changes, so this number was selected and utilized as the optimum one.

After analyzing the output parameters, the optimized parameters are given in Table 5. According to the ABC algorithm, the optimized particle for overbreak in tunnels, which is executed by drilling and blasting method, was 1.63 m^2. As indicated in Table 2, the minimum amount for overbreak was about 3.055 m^2, which was reduced as 47% compared to the original state using the optimization ABC algorithm. Moreover, the values of 4, 0.921, 1.796, 1.695, 1.242, 1.235 and 3.927 in the sequence for the number of delays, the load of the last row of the chess, the row of the first row of the hull, the intervals of the last row headers, the distance to the front end hulls, the special spending, and the length of the advance were achieved by ABC algorithm. The results indicate that by developing an ABC algorithm, the optimum values can be obtained and the overbreak values resulting from drilling and blasting in tunell can be minimized. Considering that overbreak is one of the main problems in tunneling, the reduction of this amount can contribute to have a good tunneling operation and its stability.

7 Conclusions

In the present study, using the help of AI models, prediction and optimization of overbreak in tunnel were conducted. After identifying the effective parameters in the overbreak phenomenon, eight input parameters were used to create a neural network of three types of learning function. After selecting the best model based on scoring, the selected model was used for optimization. The R^2 and RMSE values of the selected model were 0.921, 0.4820, 0.923 and 0.4277 for training and testing, respectively. The ABC algorithm, one of the new optimization algorithms, was used to optimize these parameters of the explosion pattern. Considering that overbreak is one of the main problems in tunneling, the reduction of this amount can contribute to have a good tunneling operation and its stability. After making several

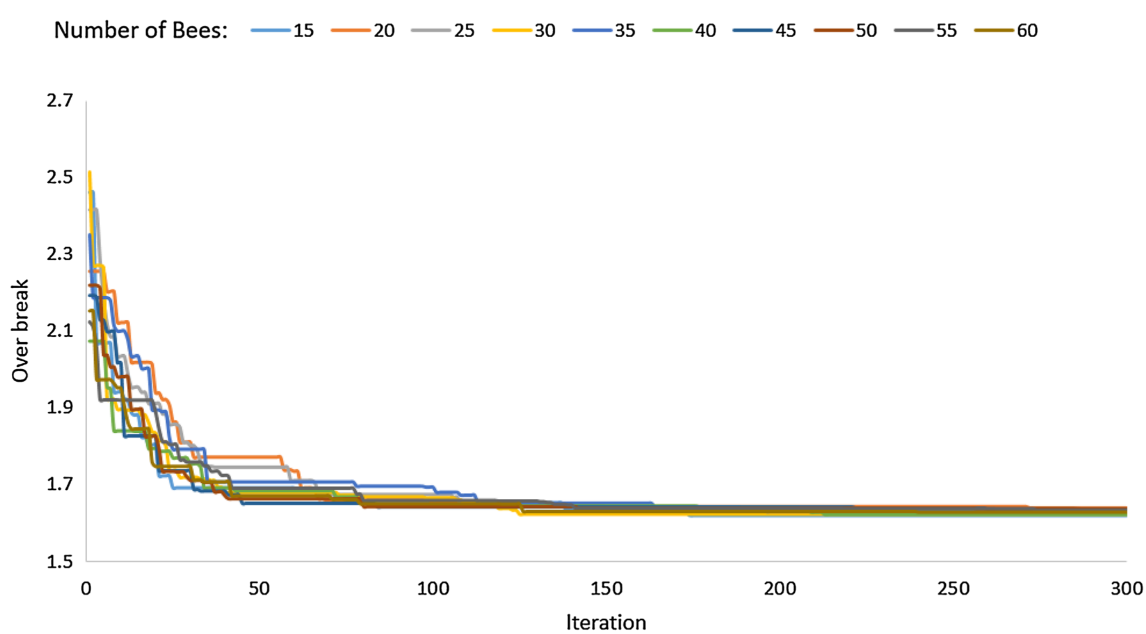

Fig. 7 The best costs of over break

Table 5 Optimized values of blast pattern parameters together with overbreak results

Parameters	Unit	Optimized value
Number of delay	–	4
Periphery burden	m	0.921
End row burden	m	1.796
Periphery spacing	m	1.695
End row spacing	m	1.242
Special charge	kg/m^3	1.235
Advanced length	m	3.927
Over break	m^2	1.63

models of optimization and variations in its weights, the optimum amount for the extra drilling was 1.63 m^2, which is 47% lower than the lowest value (3.055 m^2). Finally, this method can obtain the optimal pattern minimizing the amount of overbreak in the tunnels. It can be concluded that the developed algorithms in this study can be used in industry and practice considering ranges of model inputs with caution.

Acknowledgements The authors would like to express their sincere appreciation to the anonymous reviewers for their valuable and constructive suggestions.

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