Bull Eng Geol Environ (2019) 78:981–990
DOI 10.1007/s10064-017-1116-2

ORIGINAL PAPER

A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels

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Received: 16 May 2017 / Accepted: 27 June 2017 / Published online: 1 July 2017

Abstract Overbreak in tunnel construction creates additional costs, and it could put the safety conditions at potential risk. This paper is aimed to predict overbreak in order to control it before drilling and blasting operations through two intelligence systems, namely, an artificial neural network (ANN) and a hybrid genetic algorithm (GA)-ANN. To achieve this aim, a database comprising of 406 datasets were prepared in the Gardaneh Rokh tunnel, Iran. In these datasets, rock mass rating (RMR), spacing, burden, special drilling, number of delays, powder factor and advance length were considered as inputs while overbreak is set as output system. Many intelligence models were created to achieve higher levels of accuracy in accordance with several performance indices, i.e., root mean square error (RMSE), variance account for (VAF) and coefficient of determination (R^2). After selection of the best models, GA-ANN model results (VAF = 90.134 and 88.030, $R^2 = 0.903$ and 0.881 and RMSE = 0.058 and 0.074 for training and testing, respectively) were better compared to ANN model results (VAF = 70.319 and 68.731, $R^2 = 0.703$ and 0.693 and RMSE = 0.103 and 0.108 for training and testing, respectively). As a result, the GA-ANN predictive approach can be used for overbreak prediction with high performance capacity. Moreover, results of sensitivity analysis showed that overbreak is mainly influenced by the RMR parameter compared to other inputs.

Keywords Tunnel construction · Overbreak · Artificial neural network · Genetic algorithm

Introduction

One of the problems facing the construction of a tunnel drilling is defined as overbreak. Overbreak in the tunnel creates additional costs, and it could put the safety conditions at potential risk (Haghighi 2015). In order to predict and control overbreak induced by drilling and blasting in tunnels, many studies have been conducted. Ibarra et al. (1996) offered a relationship in terms of the Q-system and index of perimeter powder factor (PPF) for value of overbreak in Mexico. They believed that the increase in PPF can decrease the amount of overbreak and the increase of Q-system can cause increase in under break. Singh and Xavier (2005), by considering a series of experiments, investigated the amount of damage-influencing factors on overbreak and stated that all influential parameters can be categorized in three groups including rock characteristics, explosives and blasting patterns.

Based on previous investigations (Monjezi and Dehghani 2008; Jang and Topal 2013; Khandelwal and Monjezi 2013; Monjezi et al. 2013, 2014; Ebrahimi et al. 2016), many factors influence overbreak. Among all effective factors on overbreak, ratio of stemming to the burden, stemming, charge the last row to total charge, special

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charge, special charge per delay, the number of explosion rows in each stage, rock mass strength, quality index of the rock mass, rock mass weathering, groundwater conditions, especially drilling, burden, hole spacing, hole diameter, stair height and charge factor can be considered as the most influential parameters on overbreak.

Artificial intelligence (AI) techniques have been presented in the field of civil and mining engineering applications (Goh and Zhang 2012; Singh and Verma 2012; Verma and Singh 2013; Zhang and Goh 2016; Armaghani et al. 2016a, b; Ghoraba et al. 2016; Singh et al. 2016; Armaghani et al. 2016a; Tonnizam Mohamad et al. 2012). Artificial neural networks (ANNs) are a branch of AI that makes a quick resolution of problems, especially when the nature of the inputs and outputs is unknown. These networks are designed as nonlinear functions between inputs and output(s). ANNs, using samples of inputs and outputs, create relations with the use of weights and activation functions, and these relations will be used in the next samples (Haghighi 2015). These networks have changed with their changing conditions and for conditions for which a well-known algorithm between inputs and outputs does not exist. However, ANNs are associated with some limitations, i.e., slow learning rate and getting trapped in local minima (Lee et al. 1991; Wang et al. 2004). To overcome these problems, the use of optimization algorithms (OAs) like a genetic algorithm (GA) to adjust the weight and bias of ANNs for enhancing their performance prediction is of advantage. In this regard, Saghatforoush et al. (2016), by combining ANNs and an ant colony optimization algorithm, proposed a model to predict and optimize flyrock and back-break. An ANN model was developed and the proposed model was used as input for an ant colony optimization algorithm in order to optimize input parameters. Eventually, reductions of 61 and 58% were obtained for flyrock and back-break results, respectively. In addition, combination of GAs and ANNs has received attention because of their capability in solving problems of geotechnical engineering applications (Momeni et al. 2014; Mohamad et al. 2016). Momeni et al. (2014), Khandelwal and Armaghani (2016) and Mohamad et al. (2016) developed GA-ANN models for predicting pile bearing capacity, drillability of the rock and ripping production, respectively.

As far as the authors know, there is no study developing a hybrid GA-ANN model for overbreak prediction. Therefore, in this paper, to estimate overbreak induced by drilling and blasting in tunnels, a hybrid GA-ANN predictive model is constructed and proposed. To do this, the Gardaneh Rokh tunnel in Iran is considered as the case study. The mentioned tunnel is one of the most important communication tunnels between Isfahan and Shahrekord cities in Iran. In the following, after introducing the applied methods and case study, application of ANN and GA-ANN models in predicting overbreak will be discussed. At the end, the selected models will be evaluated and introduced as a suitable model for overbreak prediction.

Methods

Artificial neural networks

ANNs, which are inspired by the human brain for the purpose of data transmission, are considered as an approximation tool for solving problems of science and engineering. In general terms, applications of ANNs are useful when there is a complex and nonlinear relationship between input sample(s) and a model output (Garrett 1994; Armaghani et al. 2015). Many types of ANNs have been proposed, and the most common case is the one associated with multilayer feed-forward which contains multiple layers connected by several hidden nodes (neurons) with different connected weights (Simpson 1990). For approximating the problems, ANNs must be trained with learning algorithms. Back-propagation (BP) is the mostly commonly used algorithm for training of ANNs (Dreyfus 2005). By using BP algorithms, model error between output and target (obtained by the system) values can be minimized. When the model error is bigger than defined error like root mean square error (RMSE), the system is propagated back to adjust the network weights. A view of the structure of a BP-ANN model can be seen in Fig. 1.

Genetic algorithm

The genetic algorithm (GA), as an optimization algorithm/solution, was developed by Holland (1992). It is

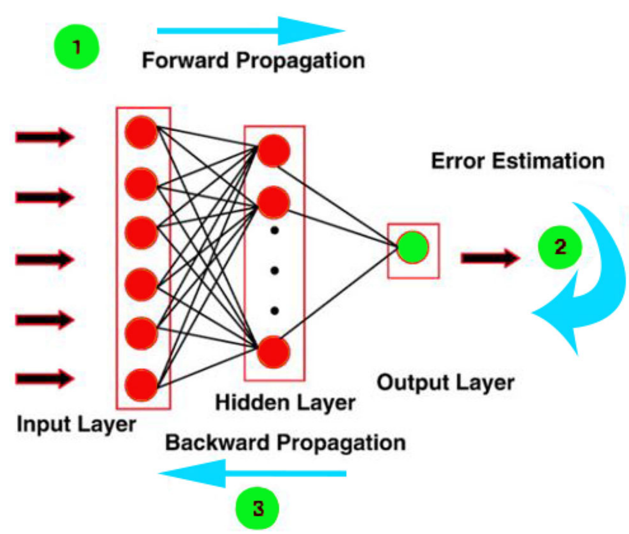

Fig. 1 A view of the structure of a BP-ANN model (Saemi et al. 2007)

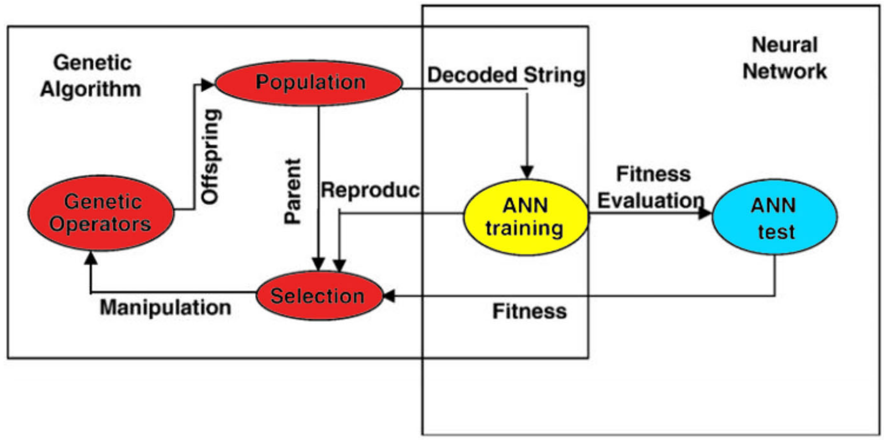

Fig. 2 Structure of a hybrid GA-ANN algorithm (Saemi et al. 2007)

based on the mechanism of natural selection and evolution of the biological species. Evaluation of the objective function in each decision is performed by the GA (Chipperfield et al. 1994). In the GA, there are a number of known individuals which can gradually lead to an optimal solution. These solutions are determined by a linear string which is composed of chromosomes (0 and 1). A generation is defined as the general solutions of population size with an optimization process in each iteration. In the GA, three operations are needed to create the next generation or generations, i.e., reproduction, cross-over and mutation. The best chromosomes are selected by a process based on scaled values known as reproduction operation. Then, the best chromosomes are transferred to the next generation directly. In the second operation or cross-over, new individuals (offspring) are created from combining special sections of individuals defined as parents. This recombination is performed based on single-point cross-over or two-point cross-over. After that, a random cross-over point and two parents in the cross-over process are selected. The production of the first individual is chosen between the left- and right-side genes of the first and second parents, respectively. For the second offspring, a reverse process is repeated as mentioned in the study conducted by Momeni et al. (2014). Finally, the mutation operator that is defined as a process for a random changing, occurs in elements of a chromosome (GOH 2000). More details regarding GA background/definition can be found in some other works (e.g., Jahed Armaghani et al. 2016; Khandelwal and Armaghani 2016).

GA-ANN combination

For increasing the efficiency and capability of ANNs by the GA algorithm, several researches have been investigated (Monjezi et al. 2012). As a result of the GA, it can be useful to adjust biases and weights of the ANN that can be caused to increase the performance prediction of the hybrid systems (Momeni et al. 2014). On the other hand, the GA in search space, finds a global minimum, and then the ANN determines the best results of the hybrid GA-ANN model. Figure 2 shows the structure of a hybrid GA-ANN algorithm.

Case study and established database

The Gardaneh Rokh tunnel is one of the most important communication tunnels in the west of Iran. The tunnel is located in 30 km from the city of Shahrekord. The length of tunnel is 1300 m with a horseshoe cross-section. With construction of the mentioned tunnel, the distance of 7000 m from Isfahan city to Shahrekord city is reduced. In addition, many of dangerous places in the road can be reduced. Figure 3 shows the location of Gardaneh Rokh tunnel in Iran. Due to short length of the tunnel, the construction method of the arch utilized the drilling and blasting technique (Fig. 4). The used blasting pattern parameters in this tunnel have been fixed along the entire length of the tunnel. Table 1 shows general specifications of excavation of the tunnel arch with a period of explosive design parameters for different conditions of rock mass.

For developing a precise hybrid intelligence model to predict overbreak, established and suitable datasets are required. Therefore, suitable model inputs should be chosen from experience and literature. Based on previous investigations, blasting pattern parameters, rock mass and material conditions and ground water factors are the most influential parameters on overbreak. In drilling and blasting operations in Gardaneh Rokh tunnel, parameters including rock mass rating (RMR), spacing (m), burden (m), special drilling (m), number of delay, powder factor (kg/m^3), advance length (m/m^3) and overbreak (m^2) were carefully measured and used in the modelling of AI models. A database composed of 406 datasets including the mentioned parameters was provided prior to modelling.

Fig. 3 Location of the Gardaneh Rokh tunnel with length of 1300 m

Statistical information including maximum, minimum, average and standard deviation (SD) of the used parameters in this study to estimate overbreak can be seen in Table 2.

Overbreak prediction

ANN modelling

As mentioned in the last section, 406 datasets (see Table 2) were utilized in AI modelling of this study. ANN capabilities depend directly on its structure, as stated by Kanellopoulos and Wilkinson (1997) and Hush (1989). Therefore, in order to have a desirable ANN model, design of an optimal structure is necessary. The number of hidden layers hidden neurons are considered as part of the structure of an ANN model. According to several studies (Hornik et al. 1989), having a hidden layer equal to one can estimate any nonlinear functions and due to that, in this paper, a hidden layer equal to one was selected. In addition, several equations, which can be used for calculation of the number of neurons in a hidden layer are presented in Table 3. Based on Table 4 and with N_i (number of inputs) = 7 and N_o (number of output) = 1, a range of 1–15 should be considered. To achieve an optimum number of neurons, many ANN models

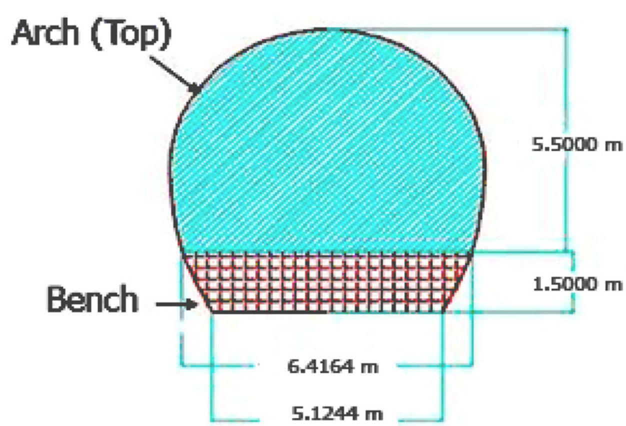

Fig. 4 Cross-section of the tunnel

were created. Tables 4 presents their results based on R^2. In that column of Table 4, average values of five runs for each hidden node can be seen. As a result, model no. 10 with 10 nodes (R^2 values of 0.684 and 0.687) provides better performance than the others. Hence, $7 \times 10 \times 1$ was chosen as the ANN structure for approximating overbreak where 7 is number of model inputs, 10 is number of neurons in the hidden layer and 1 is number of model output. The best ANN model will be selected later.

Table 1 General excavation specifications of the tunnel arch using the drilling and blasting technique

Feature	Description
Shape	Horseshoe
The cross-section of the tunnel in the arch	32.15 (m^2)
The tunnel periphery in the arch	15.052 (m)
Hole diameter	45 and 51 (mm)
The type of consumption explosive	Gelatin dynamite
Number of hole	45–85
Detonator consumption	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 (degree)
Charge of holes	Continuous
Stemming	According to the conditions stone from 15 to 60 cm

GA-ANN modelling

As stated earlier, the GA has an effective impact on ANN performance (Lee et al. 1991; Majdi and Beiki 2010). Chambers (1998) indicated that an objective function can be chosen by the GA or a hybrid GA-ANN model. Based on this process, weights and biases of an ANN can be optimized. The most effective GA parameters that were used to construct hybrid GA-ANN models should be selected/determined. Mutation probability values and percentage of recombinations were set as 25 and 9%, respectively, in the hybrid GA-ANN model. As a crossover operation, a single point with 70% possibility is used. A series of hybrid models were created in order to determine best population size (a population range of 25–600). RMSE values of the mentioned analyses showed that a population size of 300 can be performed efficiently. In these combinations, the proposed ANN architecture and generation value of 100 were used.

Table 3 Equations for number of neurons in the hidden layer

Heuristic	References
$\leq 2\times N_i + 1$	Hecht-Nielsen (1987)
$(N_i + N_o)/2$	Ripley (1993)
$\frac{2+N_o\times N_i+0.5N_o\times(N_o^2+N_i)-3}{N_i+N_o}$	Paola (1994)
$2N_i/3$	Wang (1994)
$\sqrt{N_i \times N_o}$	Masters (1993)
$2N_i$	Kaastra and Boyd (1996)
	Kanellopoulos and Wilkinson (1997)

For the next step, the maximum number of generations (G_{max}) should be identified and utilized. A parametric study was conducted to determine the effect of G_{max} on network performance. For determining the optimum number of generations, a value of 500 generations was assigned as the stopping criteria and the obtained RMSE values were considered. As shown in Fig. 5, changing of RMSE results in designing G_{max} to predict overbreak can be seen. Based on this figure, after the number of generations = 350, the network performance is unchanged. Therefore, for designing GA-ANN models, the optimum number of generations was applied as 350. In the final step, five GA-ANN models were created again and their results will be discussed later.

Evaluation of the results

In this research, different methods, i.e., GA-ANN and ANN, were conducted and proposed for overbreak estimation. Here, all 406 data sets were chosen randomly and classified as 5 different sets. As suggested by Swingler (1996), classifications of 20 and 80% were utilized randomly to separate datasets to testing and training, respectively. Then, five constructed ANN models and five constructed GA-ANN models should be evaluated using some performance indices (PIs), including R^2, amount of variance account for (VAF) and RMSE. Equations of these PIs were presented in other studies (Armaghani et al.

Table 2 Maximum, minimum, average and standard deviation of the used parameters to estimate overbreak

Parameter	Symbol	Unit	Category	Min.	Max.	Ave.	SD
Number of delays	ND	–	Input	4	10	8.54	1.48
Special drilling	SD	m	Input	0.87	2.75	2.05	0.16
Burden	B	m	Input	0.6	2	0.84	0.037
Spacing	S	m	Input	0.3	1.7	0.8	0.028
Powder factor	PF	kg/m^3	Input	0.41	1.65	1.14	0.052
Rock mass rating	RMR	–	Input	15	49	37.25	41.92
Advance length	AL	m/m^3	Input	0.5	3.96	2.19	0.33
Overbreak	OB	m^2	Output	0.23	11.21	4.69	6.09

Table 4 Training and testing results of ANN in predicting overbreak

Model no.	Nodes in hidden layer	Network result											
		R^2											
		Dataset 1		Dataset 2		Dataset 3		Dataset 4		Dataset 5		Average	
		TR	TS	TR	TS	TR	TS	TR	TS	TR	TS	TR	TS
1	1	0.503	0.386	0.476	0.488	0.473	0.488	0.477	0.471	0.499	0.385	0.486	0.444
2	2	0.539	0.608	0.546	0.592	0.543	0.599	0.533	0.465	0.569	0.528	0.546	0.558
3	3	0.579	0.499	0.592	0.680	0.583	0.579	0.621	0.492	0.608	0.511	0.596	0.552
4	4	0.617	0.553	0.588	0.584	0.624	0.526	0.637	0.576	0.610	0.617	0.615	0.571
5	5	0.638	0.627	0.620	0.670	0.623	0.553	0.617	0.608	0.634	0.634	0.627	0.618
6	6	0.657	0.483	0.680	0.576	0.660	0.574	0.650	0.592	0.660	0.647	0.662	0.575
7	7	0.670	0.652	0.670	0.646	0.697	0.589	0.686	0.626	0.687	0.575	0.682	0.618
8	8	0.683	0.591	0.700	0.641	0.656	0.608	0.633	0.655	0.623	0.592	0.659	0.617
9	9	0.626	0.595	0.666	0.595	0.682	0.599	0.707	0.619	0.686	0.623	0.673	0.606
10	10	0.667	0.732	0.663	0.670	0.703	0.693	0.679	0.669	0.708	0.673	0.684	0.687
11	11	0.672	0.684	0.702	0.662	0.674	0.662	0.667	0.657	0.657	0.686	0.675	0.670
12	12	0.702	0.601	0.661	0.667	0.700	0.525	0.687	0.631	0.653	0.529	0.681	0.591
13	13	0.637	0.553	0.647	0.626	0.666	0.550	0.682	0.602	0.697	0.570	0.666	0.580
14	14	0.670	0.573	0.694	0.593	0.691	0.640	0.681	0.709	0.672	0.596	0.681	0.622
15	15	0.633	0.622	0.660	0.653	0.691	0.625	0.693	0.626	0.700	0.637	0.675	0.633

TR training, *TS* testing

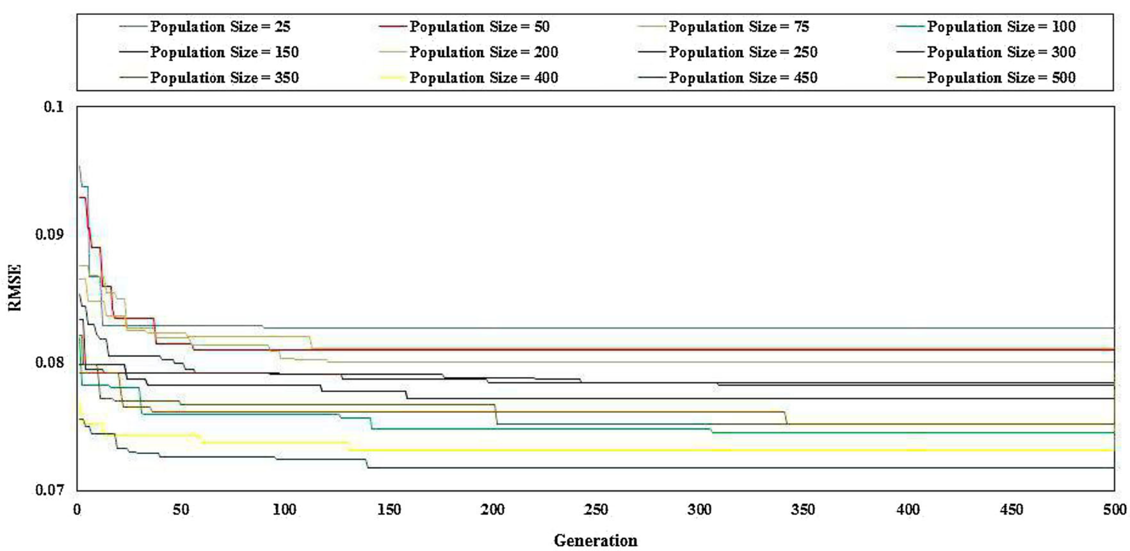

Fig. 5 Designing G_{max} of GA-ANN to predict overbreak

2017). A model is considered as perfect if $R^2 = 1$, VAF = 100% and RMSE = 0.

The values of PIs results for training and testing of datasets are tabulated in Table 5. In this table, it is not easy to identify the best model for overbreak evaluation. To solve this problem, as noted before, a simple ranking method developed by Zorlu et al. (2008) was used. More explanation regarding ranking methods can be found in other works such as Zorlu et al. (2008) and Armaghani et al. (2017). Amounts of the rankings were calculated and set for each training and testing data set separately (see Table 5). The final amounts of ratings are provided in Table 5. As shown in Table 6, model no. 3 represent the best performance of overbreak for GA-ANN and ANN methods. Based on the obtained PIs, the hybrid GA-ANN model provides better performance for prediction of

Table 5 PIs values in predicting ANN and GA-ANN models

Method	Model	R^2	RMSE	VAF	Rating for R^2	Rating for RMSE	Rating for VAF	Rank value
ANN	Tr 1	0.667	0.105	66.701	2	4	1	7
	Tr 2	0.663	0.112	66.253	1	1	2	4
	Tr 3	0.703	0.103	70.319	4	5	4	13
	Tr 4	0.672	0.108	67.186	3	2	3	8
	Tr 5	0.708	0.106	70.801	5	3	5	13
	Ts 1	0.732	0.115	72.327	5	2	5	12
	Ts 2	0.670	0.109	58.755	2	3	1	6
	Ts 3	0.693	0.108	68.731	4	4	3	11
	Ts 4	0.669	0.116	70.998	1	1	4	6
	Ts 5	0.673	0.098	65.314	3	5	2	10
GA-ANN	Tr 1	0.895	0.060	89.372	4	4	4	12
	Tr 2	0.889	0.060	89.074	2	4	3	9
	Tr 3	0.903	0.058	90.134	5	5	5	15
	Tr 4	0.888	0.064	88.733	1	2	1	4
	Tr 5	0.890	0.063	88.851	3	3	2	8
	Ts 1	0.880	0.078	88.066	1	1	3	5
	Ts 2	0.898	0.075	89.012	3	2	4	9
	Ts 3	0.881	0.074	88.030	2	3	2	7
	Ts 4	0.907	0.061	84.530	5	5	1	11
	Ts 5	0.899	0.069	89.898	4	4	5	13

Tr training, *Ts* testing

overbreak. The obtained performance predictions for the chosen models based on R^2 are displayed in Figs. 6 and 7 for ANN and GA-ANN models, respectively. Network results ($R^2 = 0.703$, $R^2 = 0.693$ for training and testing of ANN and $R^2 = 0.903$, $R^2 = 0.881$ for training and testing of GA-ANN) showed that the GA-ANN model is superior in comparison with the ANN model for overbreak estimation.

Table 6 Values of total rank for overbreak prediction

Method	Model	Total rank
ANN	1	19
	2	10
	3	24
	4	14
	5	23
GA-ANN	1	17
	2	18
	3	22
	4	15
	5	21

Parametric sensitivity analysis

Parametric sensitivity analysis is a method for checking system stability. In this study, after creation of the network, a sensitivity analysis was performed on the datasets. Sensitivity analysis examines the inclination and variation of the system related to each model input. This is performed by changing values of each input in the desired range (e.g., ±20–40%). The general equation of the mentioned sensitivity analysis is presented as follows:

$$s_k^* = s_k(a_k^*) = \left(\frac{\mathrm{d}f_k(a_k)}{\mathrm{d}a_k}\right)a_k = a_k^*\frac{a_k^*}{p^*} \quad k = 1, 2, \ldots, n, \quad (1)$$

where s_k* and k are dimensionless groups of real numbers and they are positive. The values greater than s_k* represent a greater sensitivity of index p compared to a_k. By comparing different values of s_k*, the sensitivity strength of each input parameter can be found (Zhu 2004). Using the proposed network, all parameters were checked one by one, while in each case, other parameters were fixed. It is worth noting that after performing the analyses, the mentioned parameters give a meaningful relationships with the system output. Then, changing results of the input parameters to the system output were calculated as shown in Fig. 8. As can be seen in this figure, RMR (with value of 0.91) is the most effective parameter on overbreak. In addition, the number of delays (with a value of 0.23) is the least effective parameter on the overbreak as system output of this study.

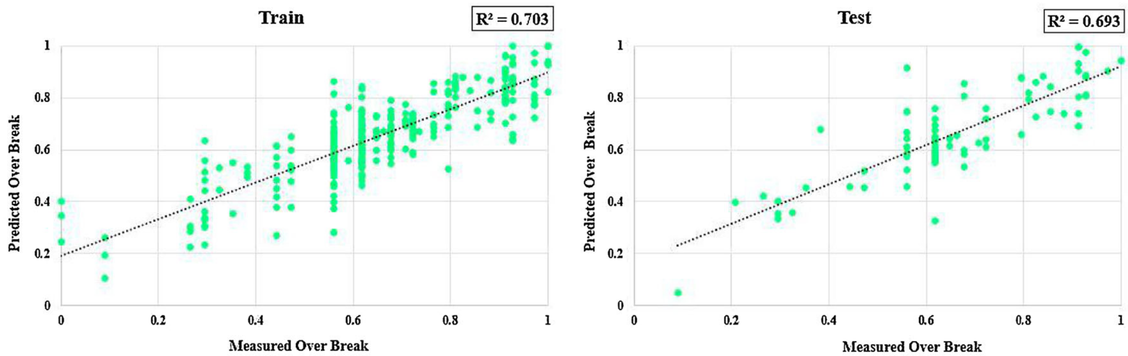

Fig. 6 The obtained performance predictions for the chosen ANN model

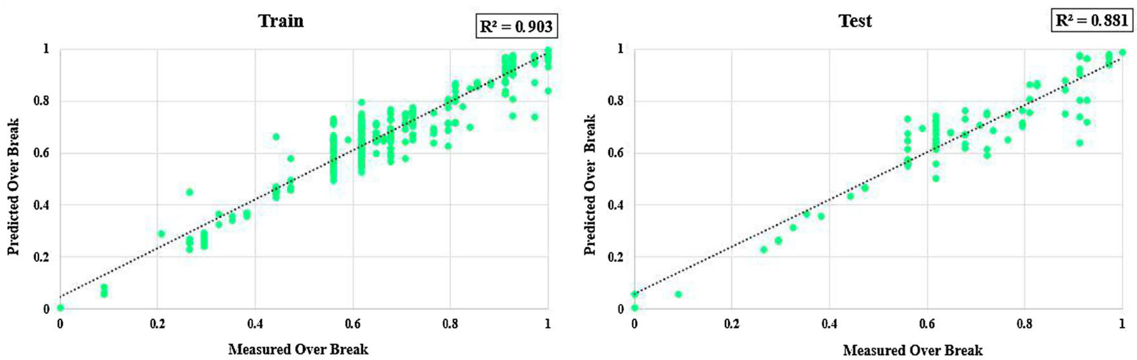

Fig. 7 The obtained performance predictions for the chosen GA-ANN model

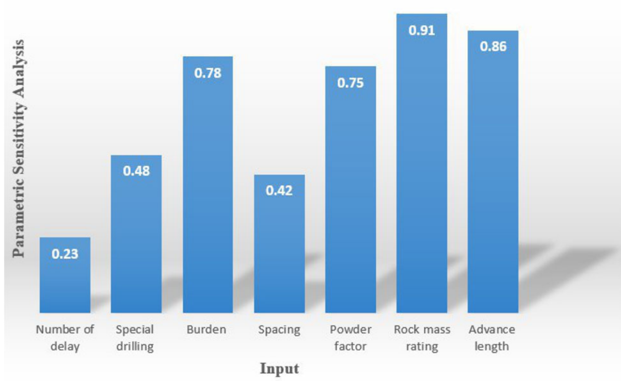

Fig. 8 Results of parametric sensitivity analysis

Conclusions

In this research, we proposed developing two AI models in estimating overbreak induced by drilling and blasting operations in tunnels. The Gardaneh Rokh tunnel, which was constructed using drilling and blasting techniques, was investigated and the relevant model inputs were measured and used in the modelling of AI techniques. The obtained results of ANN models revealed that a structure of $7 \times 10 \times 1$ produced more accurate values in overbreak prediction. Using this structure, many hybrid GA-ANN models have been created based on different GA values. Finally, after conducting a series of trial-and-error procedure, five ANN and five GA-ANN AI models were constructed in order to choose the best one among them based on the defined PIs. GA-ANN model results (VAF = 90.134 and 88.030, $R^2 = 0.903$ and 0.881 and RMSE = 0.058 and 0.074 for training and testing, respectively) were better compared to ANN model results (VAF = 70.319 and 68.731, $R^2 = 0.703$ and 0.693 and RMSE = 0.103 and 0.108 for training and testing, respectively). According to the obtained results, the GA-ANN predictive model is introduced as a new approach to predict overbreak induced by drilling and blasting operations in tunnels. By performing parametric sensitivity analysis, it was found that overbreak induced by blasting is mainly influenced by the RMR parameter compared to other inputs.

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