

Article

# Invasive Weed Optimization Technique-Based ANN to the Prediction of Rock Tensile Strength

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**Abstract:** In many site investigation phases of civil and mining engineering projects, the tensile strength of the rocks is one of the most significant parameters that must be identified. This parameter can be determined directly through laboratory tests. However, conducting such laboratory tests is costly and time consuming. In this paper, a new artificial neural network (ANN)-based model is developed to predict rock tensile strength, using the invasive weed optimization (IWO) technique. Granite samples for the purpose of this research were selected from a tunnel located in Malaysia and underwent appropriate laboratory tests (i.e., Schmidt hammer, point load, dry density, as well as the Brazilian tensile strength (BTS) as system output). A simple regression analysis was carried out, and the obtained results confirmed the need for developing a model with multiple inputs, rather than one with only a single input, in order to predict BTS values. Aiming to highlight the capability of an IWO-ANN model in estimating BTS, artificial bee colony (ABC)-ANN and imperialism competitive algorithm (ICA)-ANN were also applied and developed. The parameters required for the ANN-based models were obtained using different parametric studies. According to calculated performance indices, a new hybrid IWO-ANN model can provide a higher accuracy level for the prediction of BTS compared to the ABC-ANN and ICA-ANN models. The results showed that the IWO-ANN model is a suitable alternative solution for a robust and reliable engineering design.

**Keywords:** invasive weed optimization; artificial neural network; hybrid model; Brazilian tensile strength

## 1. Introduction

Rock tensile strength (TS) is extensively used as a significant parameter when designing a geotechnical construction, such as a tunnel [1]. Therefore, literature is consisted of numerous methods attempting to predict the TS value, either directly or indirectly. In the direct approach, the researchers or practitioners have to either make use of the empirical equations already present in the relevant literature, or gather rock specimens and then test them in laboratory [1–3]. It should be noted that it is both time consuming and costly to prepare proper rock samples with the aim of performing TS tests in

a laboratory [3]. On the other hand, in the indirect approach, the whole process can be made faster, simpler, and less costly by predicting the TS value with the help of other, less demanding laboratory experiments, e.g., the Schmidt hammer, P-wave velocity, density, and point load tests [1,4,5]. The list can be further elaborated with the Brazilian tensile strength (BTS) method, which has been proposed by the International Society for Rock Mechanics (ISRM) as an efficient method for determining TS [6].

Different researchers have suggested different empirical relations for the prediction of the TS value. Using statistical analyses, such as regression analysis and coefficients of variation, Kahraman et al. [7] attempted to determine the rock features with key impacts on the penetration rate of percussive drills. The properties they marked out as significant were the point load strength, uniaxial compressive strength (UCS), BTS, and Schmidt hammer rebound number. In addition, aiming to predict the TS value, Mishra and Basu [8] made use of two empirical methods: the block punch test and point load strength ( $I_{s50}$ ). Their findings indicated the superiority of the block punch index over  $I_{s50}$  regarding the estimation of BTS. Sheorey [9] reconfirmed the widely accepted idea that there is a correlation between BTS and UCS in rocks, and also indicated that the compressive strength of rock is roughly 10 times higher than the BTS level of the same rock. Nevertheless, rock has a site-specific behavior. Kahraman et al. [2] was mainly focused on how UCS and BTS are related to each other in various types of rock; the relative study resulted in finding a linear correlation between the two factors. Heidari et al. [3] compared all point load testing methods proposed in the literature in terms of their use in practical applications. They made use of the diametral, axial, and irregular methods for the purpose of predicting  $I_{s50}$ . A comparison was made on the obtained results, and a number of equations were developed in a way to both practically and economically estimate the BTS value.

In addition, aiming to determine how directly TS and BTS are related to each other, Perras and Diederichs [10] analyzed rocks' TS. They also made a comprehensive review of the methods used to measure direct TS, BTS, and alternative methods for the estimation of a rock's TS. Their results showed that laboratory tests cannot be easily applied for the accurate prediction of rock TS. Armaghani et al. [11] carried out a number of laboratory tests on a total of 87 granite-type samples in order to predict their BTS value. They only made use of simple and multiple regressions for this purpose due to the high expense and time requirement of laboratory tests. Their findings showed a higher capability of multiple regression models compared to simple regression ones in terms of the accuracy level in the BTS prediction. The literature also contains great efforts for the development of intelligent systems aiming to be applicable to approximating science and to provide a solution to problems that may arise in engineering contexts [12–56].

Furthermore, a number of significant studies have been carried out with similar objectives with the present paper. Both artificial neural networks (ANNs) and statistical methods were employed by Singh et al. [4] in order to predict TS in schistose rocks. They confirmed the higher accuracy level of ANNs compared to conventional methods regarding TS prediction. Likewise, ANNs are able to generalize results, while the conventional methods fail to do this. Baykasoğlu et al. [1] investigated the drawbacks of the artificial intelligent methods previously introduced in the literature, and for the first time applied various sets of genetic programming to experimental data aiming to predict limestone strength. In another project, a general prediction model was developed by Kumar et al. [57] in order to predict the values of UCS and BTS formed by rotary drilling into sedimentary rock. For the purpose of constructing and evaluating their proposed model, they utilized multiple regression analyses and prediction performance indices, respectively. They concluded that the model could be effectively applied to real-life situations. It is true that the ANN is a capable technique for solving/addressing engineering problems/issues; however, they are also subject to certain limitations, including low learning speed and an incapability to escape from local minima [58,59]. To remove these disadvantages, ANN can be integrated with optimization algorithms, such as artificial bee colony (ABC), imperialist competitive algorithm (ICA), invasive weed optimization (IWO), and particle swarm optimization (PSO). In this manner, ANNs can perform in their prediction tasks with a higher efficiency through the adjustment of their bias and weight. In recent years, such hybrid systems have been applied to

a number of geotechnical problems (see [60–62]). Based on the above discussion, the present paper attempts to accomplish the following objectives:

1. To create an appropriate database applicable for the prediction of TS.
2. To develop a number of novel equations by means of simple regression analysis.
3. To design three hybrid intelligent models: IWO-ANN, ABC-ANN, and ICA-ANN.
4. To propose a hybrid intelligent model of the highest accuracy in predicting rock TS.

## 2. Laboratory Experiments and Regression Analysis

For the purpose of the research presented herein, a total of 100 granite samples were gathered from the Pahang Selangor Raw Water Tunnel (PSRWT) in Malaysia. Different rock index tests, i.e., the Schmidt hammer test (Rn), the dry density (DD) test, the point load test ( $Is_{50}$ ), as well as BTS were conducted in the laboratory, based on the ISRM standards [6]. In this research, a total of 80 datasets were provided in order to perform modeling and required analyses. Figure 1 summarizes the input and output datasets used. This figure also shows the relationship matrix between all data.

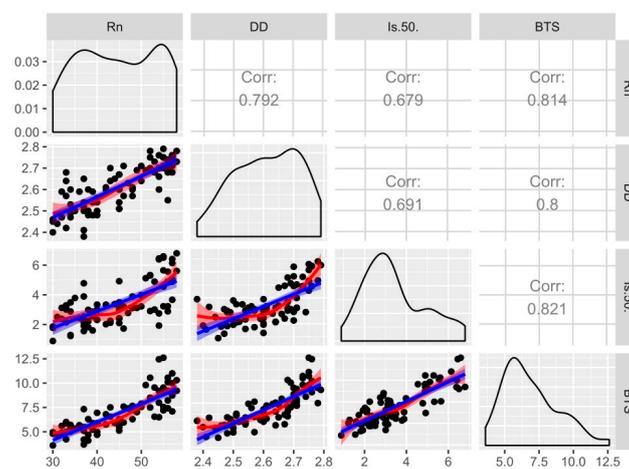
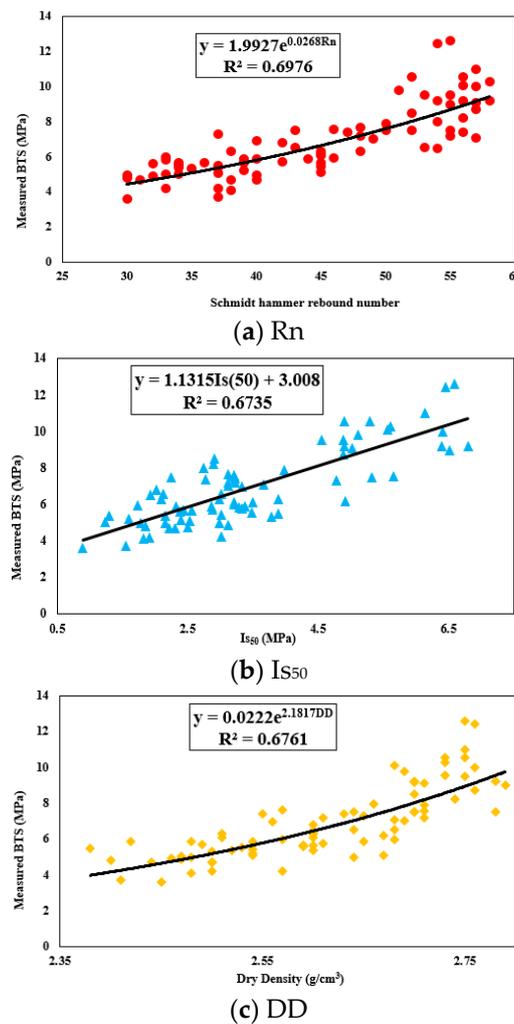


Figure 1. General information related to data.

Simple regression models were utilized for the purpose of identifying the relationship between the model inputs ( $Is_{50}$ , DD, and Rn) and the system output (BTS). A variety of equations, including power, linear, and exponential, were tested for the evaluation and selection of the most appropriate type of equation for the prediction of TS. The equations were evaluated with taking into consideration some prediction intervals (PIs) such as variance accounted for (VAF), root mean square error (RMSE), and  $R^2$ , which have been recommended by lots of researchers such as [24,59,61,63]. In addition, the formulas in regard to such PIs were taken from Mohamad et al.'s [64] research. It is noted that the best fit is the one with a VAF of 100%, RMSE of 0, and  $R^2$  of 1. The equations used for the prediction of BTS, as well as their PIs, are listed in Figure 2. Selection of the equations was on the basis of their PIs results in comparison with other types of equations. For example, as can easily be noticed,  $R^2$  was calculated as 0.698, 0.674, and 0.676, for Rn,  $Is_{50}$ , and DD, respectively. Figure 2 demonstrates the graphs of the equations that were developed for the TS prediction. The obtained results were found significant; however, aiming to achieve TS prediction results of a higher accuracy in real-life situations, it is necessary to develop a number of new models. Accordingly, three intelligent models, i.e., ABC integrated with ANN (ABC-ANN), IWO integrated with ANN (IWO-ANN), and ICA integrated with ANN (ICA-ANN) are constructed for the purpose of predicting the BTS of the granite type rock samples.



**Figure 2.** The best simple regression based on the (a) Schmidt hammer test (Rn), (b) point load test (IS<sub>50</sub>) and (c) dry density (DD).

### 3. Methodology

#### 3.1. Imperialist Competitive Algorithm

Atashpaz-Gargari and Lucas [65] pioneered the imperialist competitive algorithm (ICA) as an algorithm based on global search population and implemented to be effectively applicable for optimization problems. ICA starts with randomly generating the initial population denoted by countries. Thus, N number of countries ( $N_{country}$ ) are produced. After that, the number of imperialists, i.e.,  $N_{imp}$ , needs to be chosen as a certain number of the countries with minimum costs. The other countries ( $N_{col}$ ) in the system are employed as special functions amongst the other empires. Generally, the greater the number of colonies, the more powerful imperialists one will have. ICA is mainly consisted of three operators: assimilation, revolution, and competition [66–68]. A part of ICA is the colonies attracted similarly by existing imperialists, which means that the existing imperialists control the part of the initial colonies before any process. On the other hand, revolution makes big changes in the system. Through the competition procedure, the imperialists strive to acquire as many colonies as possible. Any empire that would be capable of achieving the predefined criteria is finally a winner. Such a process is iterated until the end of the desired benchmark. In ICA, the decades' number has a process comparable to the number of particles in PSO and also that of generations in GA. To design them, it will be helpful to evaluate the outcomes obtained from the root mean square (RMSE). For a

detailed explanation regarding ICA, one may refer to several studies in the literature [60,65,69]. An ICA structure is depicted in Figure 3.

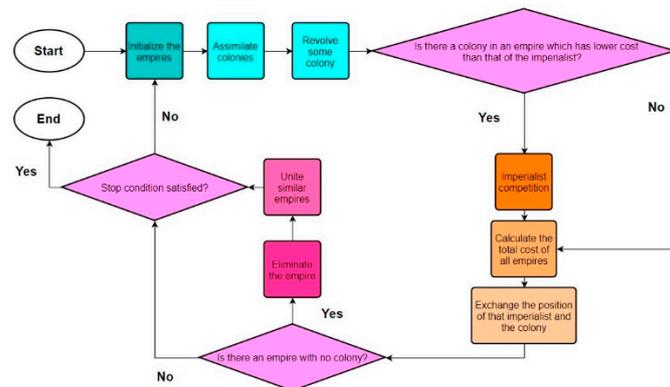


Figure 3. Imperialism competitive algorithm (ICA) flowchart.

### 3.2. Artificial Bee Colony

ABC is an optimization algorithm inspired by the bees’ social life and developed by Karaboga [70]. Each bee in this algorithm signifies a simple component. In case they form a bee colony, they will show a complex coherent behavior that will be capable of shaping an integrated system to discover and exploit the nectars of flowers. Each of the colonies contains three groups of bees, each of which has a certain task. The bees in the first group are scouts whose responsibility is to discover new sources of food. The scouts search in a random way throughout the outlying environment, and when they find a source, they will memorize the place. When each bee comes back to its hive, the bees existing within the hive share their information in regard to discovered sources with each other doing a waggle dance. Afterwards, several bees will be sent to exploit the sources. The bees within the second group are employed bees. Their responsibility is the exploitation of the predetermined food sources. The bees in the third group are onlooker bees. They stay in the hive waiting for the other bees; when information is exchanged with the other bees by waggle dance, they will select a resource in accordance with the fitness of the answer for exploitation.

ABC has the required capacity to solve numerous mathematical and engineering issues, e.g., optimizing the wells locations in oil basins [71], in cases where water is discharged from a dam [72], classification of data into clusters [73], and scheduling of machines [74], accidental failure of a nuclear power plant [75]. It can also be integrated with ANNs in order to predict the bottom pressure of wells along the network [76]. In the context of geotechnical engineering field, this algorithm has been merely applied to the prediction of the blast-induced back break [77]. Four steps are involved in ABC as follows [62,78,79].

First step: Initially, 50% of the bees living in the hive are considered as employed bees and the rest of them are non-employed ones. Just a bunch of the employed bees is assigned to each one of the explored food sources. That is, the employed bees equal the quantity of food sources. As a result, one employed bee is allocated to each of the available sources. In other words, inside the answer scope, existing food sources form the initial solution. When the initial solutions are created, each solution’s value needs to be computed considering the relationship of the problem.

Second step: For each solution, a new response can be formed using the following equation:

$$\begin{aligned}
 v_{i,j} &= x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) \\
 i &\in \{1, 2, \dots, BN\} \\
 j &\in \{1, 2, \dots, D\} \\
 k &\in \{1, 2, \dots, BN\} \ \& \ k \neq i \\
 \varphi &\in [-1, 1]
 \end{aligned}
 \tag{1}$$

where

- $x_{i,j}$  is the response  $i$  for the parameter  $j$ ,
- $v_{i,j}$  is parameter  $j$  in the new response,
- $i$  is the number of one to the number of solutions,
- $\varphi$  is a random number in the negative interval of 1-1,
- $k$  is a random number of one the answers or solutions,
- $BN$  is the number of initial solutions,
- $D$  is the number of optimization parameters.

When a new answer/response is formed, in case this answer's value exceeds the former answer's value, it will be substituted; if not, the answer will be forgotten.

Third step: The probability of bees coming from each of the defined sites will be computed using the equation below:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{2}$$

where  $fit_i$  signifies the source of the fitness of source  $i$  and  $p_i$  denotes the choice probability of source  $i$  by the onlooker bees. With respect to each item's fitness, some are assigned. All the bees in this step might be dedicated to a certain food site based on the basis of the fitness value. When each source's value is computed by means of Equation (1), a fresh answer is created for the answers chosen. In case the value of this answer exceeds that of the former one, the former answer will be replaced with the new one; if not, it will be fined. The goal of the use of the fine is that a count is made for the number of failures in order to enhance the response; if the answer is not enhanced as desired, it will be added with one unit.

Step 4: In case the non-improvement answer counter reaches up to a predefined value ( $C_{max}$ ), the answer should be substituted with a randomly selected answer. In addition, the criteria for termination of the repetitions are also checked in this step, whether they have been met or not. If yes, the repetitions end; if not, it goes back to the second step. For more detailed information about ABC and the way it operates, one may refer to literature (e.g., [62,80]). A flowchart of ABC is depicted in Figure 4.

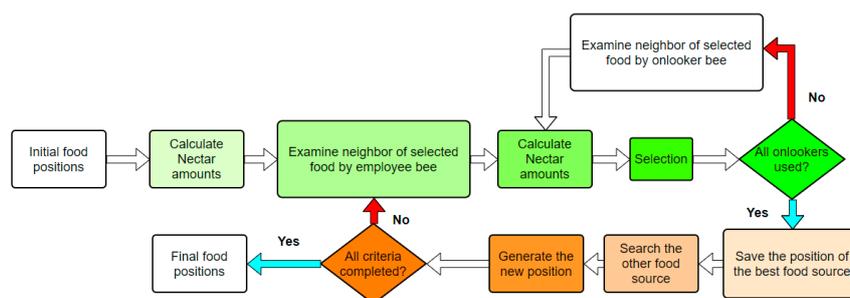


Figure 4. Artificial bee colony (ABC) flowchart.

### 3.3. Invasive Weed Optimization (IWO)

As a population-based optimization technique, the invasive weed optimization (IWO) is able to satisfy the excellent performance of a mathematical equation in a way of both adaptation and randomization of a weed colony. As a fact, the great growth of the weeds (as very strong herbs) is considered as an important threat to plant products. Actually, their level of resistance against environmental and climate changes is high. So, according to its features, a robust optimization algorithm is achieved. In IWO, the weed community and their compatibility, resistance, and randomness try to solve a problem.

In respect to the IWO background, IWO was developed based on an agriculture phenomenon that is inspired by the invasive weed colonies. As explained before in the other way, weed (as a plant)

is able to grow unintentionally. There are many benefits of weeds' existence in urban spaces and else. However, if the unintentional grow of this plant includes some damages for human activities or the planet, it is considered as a "weed" [81]. Although IWO is a simple algorithm in terms of structure, concept, and implementation, it is a powerful optimization technique to solve almost all optimization problems. In order to have a better understanding about weeds and their habitat behavior, the following steps are important to explain:

(1) In the first step with name of "population initialization", a number of seeds are partially spread in the search space.

(2) The second step or "reproduction" will start with the pouring of every plant into a flowering plant; then, the system is able to generate seeds that are worth their proportion. Subsequently, the number of plant seeds will linearly decrease from  $S_{max}$  to  $S_{min}$  using the following equation:

$$n(w_i) = \frac{S_{max}(\max fit - fit(w_i)) + S_{min}(fit(w_i) - \min fit)}{\max fit - \min fit} \tag{3}$$

(3) The third stage is related to determinations of new positions of the seeds in the search space. In this step, the child's seeds will be located around their parents.

(4) Step number 4 (or competitive elimination stage) is related to creation of the best seeds according to their merit. In fact, this will happen if the number of existing created seeds reach a certain level ( $P_{max}$ ).

(5) In the final stage, if the conditions are not fulfilled, in order to finish the process, the steps from the second stage will be repeated; otherwise, the execution of the algorithm ends. To have a better understanding of IWO step implementation, Figure 5 shows a general diagram for an invasive weed algorithm.

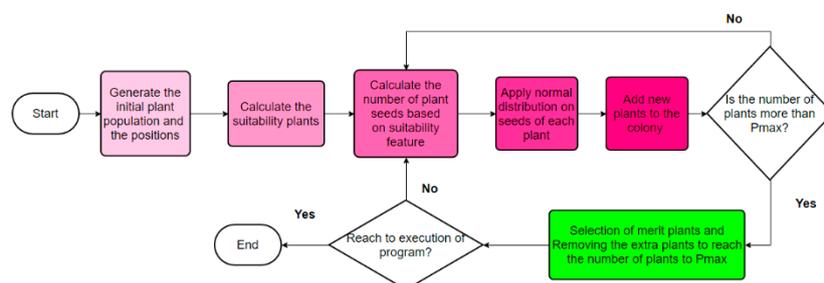
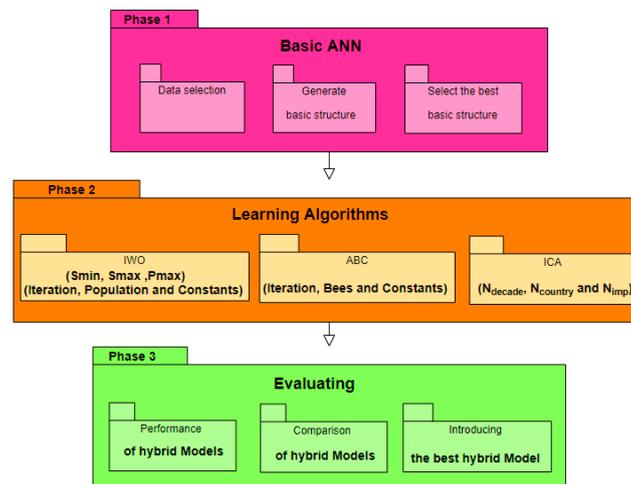


Figure 5. Invasive weed optimization (IWO) flowchart.

### 3.4. Hybrid Algorithms

The literature contains numerous studies conducted to improve ANN using optimization algorithms such as PSO, genetic algorithm (GA), ICA, and ABC (see [38,61–65]). The back-propagation (BP) does not act strongly in exploring the accurate global minimum; as a result, the ANN model might obtain unwanted results [82–88]. However, there is a higher probability for ANN to be trapped in local minima. In order to solve ANN problems and get a higher level of performance prediction, the weights and biases of ANNs should be optimized by implementing optimization algorithms such as ICA, ABC, and IWO. In particular, the hybrid ICA-ANN, ABC-ANN, and IWO-ANN models do not get caught in the local minima due to the robustness of the optimization algorithms. However, the power level of each hybrid algorithm depends on the power level of its optimization techniques i.e., ICA, ABC, and IWO. Therefore, the structure of optimization technique as well as their most effective parameters play an important role on results of hybrid ANN-based models. As shown in Figure 6, the most effective parameters on each optimization algorithm are presented. The present paper develops three hybrid models for the purpose of predicting TS: IWO-ANN, ICA-ANN, and ABC-ANN. In these hybrid models, IWO, ICA, and ABC are responsible for exploring global minimum; after that, ANN chooses it in a way to obtain the best results. Actually, the basic optimization algorithms were used to form new

combinations, and they were connected to ANN. Then, different parametric studies were conducted to obtain the best combination for each hybrid model. It is important to mention that the source of optimization codes was taken from their original studies. Figure 6 shows three stages of analysis to predict the BTS of the rock samples. The first stage of the analysis is related to ANN structure selection. In the second stage, the best structures of optimization algorithms should be selected based on the most important mentioned parameters on them. Then, in the last stage, the hybrid ANN-based models were evaluated using the most important performance indices.



**Figure 6.** Modeling procedures of hybrid artificial neural network (ANN)-based techniques in predicting Brazilian tensile strength (BTS).

#### 4. Model Development

Hybrid model processes are presented in this section. Three hybrid models that are based on the combination of the base model (ANN) with the algorithms of IWO, ABC, and ICA are discussed. To design the best model to predict the TS, each model is separately evaluated to identify the best performance of each.

##### 4.1. ICA-ANN

To achieve an ICA-ANN model of the highest quality, the ICA parameters need to be completely investigated, but first, the architecture of ANN must be fully determined. The performance of the ANN models depends strongly on the suggested architecture of the network [89–91]. Therefore, determination of the optimal architecture is required to design an ANN model. The network architecture is defined as the number of hidden layer(s) and the number of nodes in each hidden layer(s). According to various researchers (e.g., [92–94]), one hidden layer can solve any complex function in a network. Hence, in this study, one hidden layer was selected to construct the ANN models. In addition, determining the neuron number(s) in the hidden layer is the most critical task in the ANN architecture, as mentioned by Sonmez et al. [95]. It was performed through a trial and error procedure, which finally resulted in the fact that an architecture of  $3 \times 5 \times 1$  (or a model with five hidden neurons) can offer optimum results. Thus, the above architecture was considered for the best ANN model as well as for all hybrid ANN-based models (as a confirmed initial ANN model) developed in this study. More information on obtaining ANN structures can be found in previous articles [96–100].

As noted previously, the key parameters in ICA are  $N_{decade}$ ,  $N_{country}$ , and  $N_{imp}$ . To set the  $N_{imp}$  value, lots of models were designed by means of different values of this parameter ranging from 15 to 40 with an incremental step of five. In these models,  $N_{country}$  was set to 200, and  $N_{decade}$  was set to 150. The results obtained from such a parametric research confirmed that when  $N_{imp}$  is set to 25, a higher performance capacity can be achieved. On the other hand, for the purpose of choosing an optimal value for  $N_{decade}$ , as can be seen in Figure 7, different models were created with  $N_{country}$  values ranging

between 50 and 400, with an incremental step of 50. The models' performance was then tested based on their RMSE. The RMSE results did not change any more after  $N_{decade} = 550$ . Finally, with the two parameters of  $N_{imp} = 25$  and  $N_{decade} = 550$ , different numbers of countries were taken into account, and their ICA-ANN models were configured. Required evaluations were done on the models on the basis of the performance indices (PIs), i.e., RMSE values and the coefficient of determination ( $R^2$ ) (see Table 1). To select the hybrid models of the highest quality in this research, Zorlu et al.'s [101] ranking method was adopted.

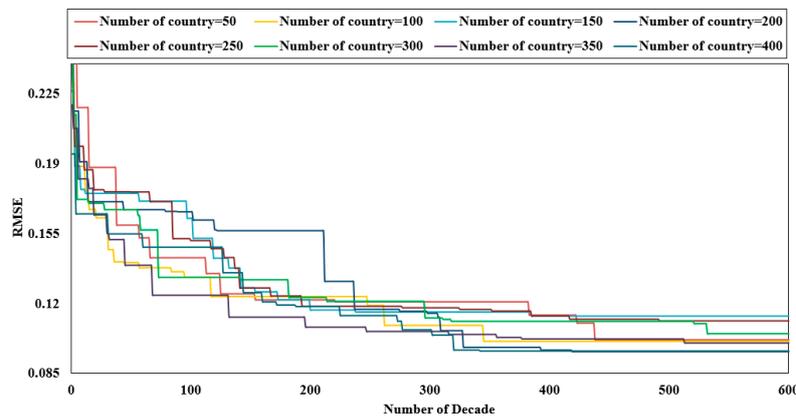


Figure 7. Hybrid models of ICA with various  $N_{country}$  numbers.

Table 1. Investigating the effects of various  $N_{country}$  in predicting BTS.

Model No.	$N_{country}$	Network Result				Ranking				Total Rank
		TR		TS		TR		TS		
		$R^2$	RMSE	$R^2$	RMSE	$R^2$	RMSE	$R^2$	RMSE	
1	50	0.865	0.1019	0.877	0.1104	4	4	3	3	14
2	100	0.871	0.1012	0.882	0.1001	5	5	4	4	18
3	150	0.853	0.1136	0.863	0.1187	1	1	1	1	4
4	200	0.899	0.096	0.901	0.0978	8	8	7	7	30
5	250	0.857	0.1113	0.871	0.1119	2	2	2	2	8
6	300	0.861	0.1049	0.902	0.0971	3	3	8	8	24
7	350	0.874	0.1003	0.899	0.0983	6	6	6	6	24
8	400	0.898	0.0964	0.885	0.0997	7	7	5	5	24

TR: Training, TS: Testing.

This technique is fully explained by Zorlu et al. [101], based on which a rank value was allocated to each PI in its group (training and testing). For instance, values of 0.865, 0.871, 0.853, 0.899, 0.857, 0.861, 0.874, and 0.894 were obtained for the  $R^2$  values of training datasets of models 1 to 8, respectively, and values of 4, 5, 1, 8, 2, 3, 6, and 7 were set to their ranks, respectively. This process was also done in the case of the RMSE results. Afterwards, a summation value of rating of the  $R^2$  train, RMSE train,  $R^2$  test, and RMSE test was computed and allocated to each model, according to which model 4 ( $N_{country} = 200$ ) with a total rank of 30 was found to be the best ICA-ANN model. An evaluation of the best ICA-ANN results is presented in the next sections. All the models were configured by means of a ratio of 80 to 20 for the training and testing datasets, respectively.

In this study, a certain color was dedicated to each row of the models. As the red color intensifies, it achieves a higher score than the rest of the scores within that column; on the other hand, the less intensified color shows that the parameter is lower than the other parameters in the column. For instance, model number 5 of ICA-ANN reflexes a high intensified red in the  $R^2$  column of the training section. Using such an approach, the best parameters were determined in each of the columns, and in the last one, an item with a collectively higher quality (concerning the red color intensity) was chosen.

In Table 1, this system is observable. This way, the novel method is employed for the purpose of choosing the best models. To adopt this method in an effective way, we made use of coding in order to determine the colors' intensity. It is worth mentioning that the use of the ranking system leads to the achievement of the same result. However, this innovative method of exploring the models of highest quality among others can be recognized as a novel and smart solution to the selection and categorization of models. Such a method of categorization is termed as a color intensity rating (CIR) system. This system was also applied to the results obtained from the other hybrid models developed in this paper. The application of this method can be found in some research [62,80].

#### 4.2. ABC-ANN

To enhance the ANN performance, the ABC algorithm was also used. Generally, the BP algorithm is employed by researchers aiming at training ANN. BP suffers from a number of deficiencies that decreases the ANN performance quality. At the time the network is searching for the best system weights, errors must be minimized. In this regard, ABC searches for appropriate weights and optimizes them. An increase in the number of bees allows them to detect in a wider area. Such a process is continued until the algorithm can obtain minimum error. Each time the selection is done, the values remain constant, awaiting a better result to be achieved for the network weights. Under such conditions, various models were formed, each of which iterated its operation for 600 rounds in order to obtain results of higher reliability. Different bees can be observed in Figure 8.

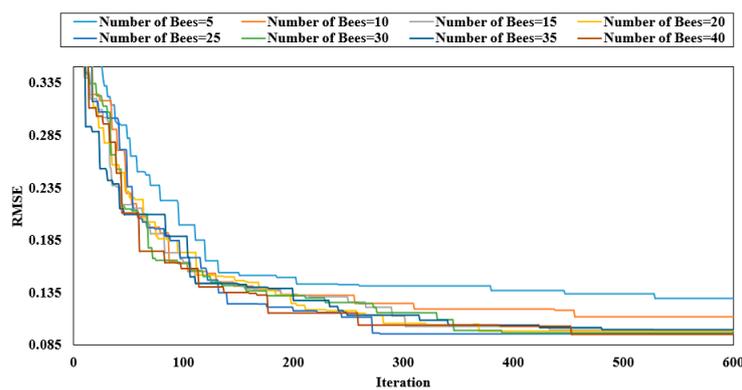


Figure 8. Hybrid models of artificial bee colony (ABC) with various bee sizes.

As can be seen in Figure 8, the number of bees ranged between 5 and 40 in order to examine the effect of the number of bees. Better results are expected to be obtained with an increase in the number of bees, although when the operation of the algorithm is iterated for 500 times, almost all the answers coincide. It is because bees typically gather in spots wherein the best answer lays. It makes this algorithm faster than the other ones, and the resultant answer is typically of a higher performance quality.

Table 2 presents the values achieved from the ABC-ANN model in terms of the TS prediction in BTS. Based on the rating method, model number 8, which consisted of 40 bees, was the best one regarding the total  $R^2$  and RMSE scores. In case of the training and testing model number 8, the values of  $R^2$  and RMSE were 0.908, 0.0951, 0.904, and 0.0952, respectively.

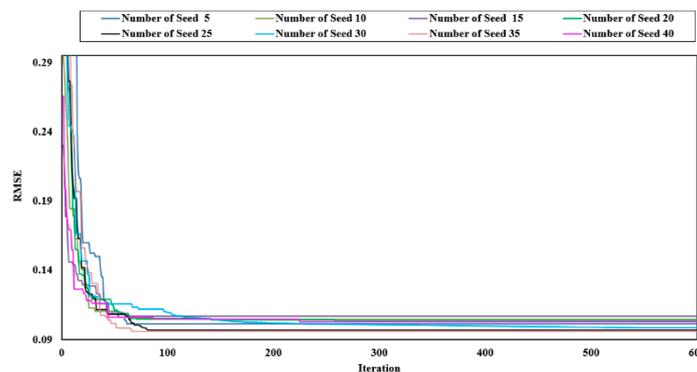
**Table 2.** Investigating effects of various bees in predicting BTS.

Model No.	Bees No.	Network Result				Ranking				Total Rank
		TR		TS		TR		TS		
		R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	
1	5	0.843	0.1295	0.854	0.1264	1	1	1	1	4
2	10	0.857	0.1122	0.867	0.1091	2	2	2	2	8
3	15	0.896	0.0987	0.899	0.0971	5	5	6	6	22
4	20	0.895	0.0986	0.879	0.0995	4	4	3	3	14
5	25	0.906	0.0959	0.902	0.0963	7	7	7	7	28
6	30	0.901	0.097	0.894	0.0978	6	6	5	5	22
7	35	0.875	0.1001	0.891	0.0988	3	3	4	4	14
8	40	0.908	0.0946	0.904	0.0955	8	8	8	8	32

TR: Training, TS: Testing.

### 4.3. IWO-ANN

In this section, the new IWO-ANN model is implemented. According to our literature review, there is no research yet that has combined these two algorithms. However, the implementation steps of this new model are similar to previous models. The IWO algorithm described above is known as a new optimization algorithm that is used for optimization in various issues. Various parameters are involved in this algorithm; some of its most important ones, include the number of iterations, the initial population of seeds, and so on. Some of these parameters have less impact on the results and can be obtained by trial and error methods. Therefore, these parameters are initially determined. The minimum and maximum number of seeds ( $S_{min}$  and  $S_{max}$ ) were investigated from zero to 30. In this case, the  $S_{min}$  value is zero, and the best condition for the  $S_{max}$  is 20. The initial and final value of standard deviation parameter actually helps to knock off the selection, using the variance reduction exponent parameter. Values of 0.5, 0.001, and 4 were selected for these three parameters (the initial and final value of standard deviation and the variance reduction exponent parameters), respectively. Finally, the main parameters such as the number of iterations and the final number of plants were determined according to Figure 9. To compare the number of iterations, similar to those presented in the previous sections, 600 iterations were selected for all the models. As shown in Figure 9, the RMSE of the models changes up to 300 iterations, and after that, they reach a constant level. For this reason, 300 iterations is the optimum value for designing next models. Finally, different models of plant seeds were designed (5–40), the results of which are presented in Table 3. Using this table, the best model is selected. As can be obtained, model number 7 provides the best conditions for TS prediction.



**Figure 9.** Hybrid models of invasive weed optimization (IWO) with various seed numbers.

**Table 3.** Investigating effects of various seeds in predicting BTS.

Model No.	Seeds No.	Network Result				Ranking				Total Rank
		TR		TS		TR		TS		
		R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	R <sup>2</sup>	RMSE	
1	5	0.898	0.0964	0.889	0.0971	5	5	4	4	18
2	10	0.869	0.0998	0.881	0.0988	2	2	3	3	10
3	15	0.861	0.1018	0.877	0.1004	1	1	2	2	6
4	20	0.874	0.0987	0.869	0.1028	3	3	1	1	8
5	25	0.923	0.0918	0.909	0.0943	7	7	6	6	26
6	30	0.909	0.0935	0.922	0.0927	6	6	8	8	28
7	35	0.928	0.0911	0.917	0.0936	8	8	7	7	30
8	40	0.887	0.0979	0.894	0.0959	4	4	5	5	18

TR: Training, TS: Testing.

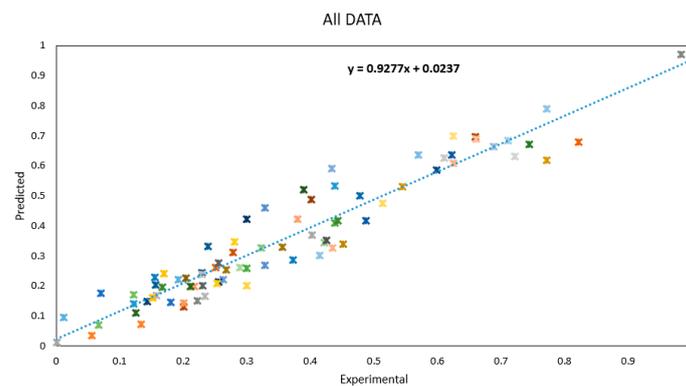
### 5. Results and Discussion

Findings of the simple regression analysis carried out in this study demonstrated that there is a need for predictive models to make precise estimations regarding rock TS. To this end, the present paper presents three hybrid models. In the proposed models, three neurons were utilized within the input layer, i.e., Rn, DD, and Is<sub>50</sub>, while the BTS values were utilized in the output layer. Through a trial-and-error method, it was found that when the number of neurons within the hidden layer was set to five, the model performance was better than the other conditions. Aiming at choosing the best hybrid IWO-ANN, ABC-ANN, and ICA-ANN models, we developed numerous models on the basis of the results obtained from a number of parametric studies. At the final step, amongst the three hybrid models, the best one was chosen on the basis of the models' system error performance. In addition, more evaluations were conducted on the chosen models through comparing between the other PIs, i.e., R<sup>2</sup> and VAF. Table 4 presents the PI values of all hybrid models. Furthermore, Table 4 show the difference between the values achieved from the measured and predicted TS values of the rocks by means of IWO-ANN, ABC-ANN, and ICA-ANN, respectively. As can be concluded from Table 4, the IWO-ANN outperformed the other optimum hybrid models in terms of all the PIs. That is, IWO-ANN returned the most accurate values (i.e., the lowest RMSE with the maximum values of VAF and R<sup>2</sup>) for the training and testing datasets. For instance, in regard to testing the datasets, the IWO-ANN model with the RMSE of 0.0911, R<sup>2</sup> of 0.917, and a VAF of 91.731 estimated the BTS more accurately compared to ABC-ANN with the RMSE of 0.0955, R<sup>2</sup> of 0.904, and a VAF of 90.419. In addition, it presented a higher quality performance in comparison to ICA-ANN with an RMSE of 0.0978, R<sup>2</sup> of 0.901, and VAF of 90.134. Therefore, although all of the above-mentioned models were found to be capable of predicting the BTS value with an acceptable level of precision, the IWO-ANN model performed the best. Obviously, the IWO-ANN model for the rock TS prediction can be taken into account as an innovative predictive model in engineering fields of study. Finally, Figure 10 shows the prediction results for the IWO-ANN model for all the samples. In this figure, given that all the laboratory samples are in the new IWO-ANN system, a careful evaluation of the final accuracy is obtained. A linear relationship between the actual (parameter x) and the predicted (parameter y) value is also given. As expected, the chosen model presents as a new solution to the tensile strength of the rock samples in future works according to defined conditions for system design.

**Table 4.** Results of hybrid models. RMSE: root mean square error, VAF: variance accounted for.

Hybrid Model	R <sup>2</sup>		VAF		RMSE	
	TR	TS	TR	TS	TR	TS
IWO-ANN	0.928	0.917	92.872	91.731	0.0911	0.0936
ABC-ANN	0.908	0.904	90.816	90.419	0.0946	0.0955
ICA-ANN	0.899	0.901	89.889	90.134	0.0960	0.0978

TR: Training, TS: Testing.

**Figure 10.** Prediction results of the best IWO-ANN model for all samples.

## 6. Conclusions

The level of tensile strength (TS) of rock in various tunnel and civil engineering projects is considered as an important part in the design factor. However, performing actual tensile strength tests in a lab is sometimes costly and always complex. Therefore, recently, various techniques have been developed aiming to evaluate this parameter through other, more easily applicable, measurement techniques. The present study developed three hybrid intelligent predictive models, i.e., IWO-ANN, ICA-ANN, and ABC-ANN aiming at accurately predicting the tensile strength (TS) of the granitic rock samples based on the values of the Schmidt hammer test (Rn), the dry density (DD) test, and the point load test (Is<sub>50</sub>). First, a substantial relationship was explored between the inputs and output using simple regression analysis. The R<sup>2</sup> results of roughly 0.7 for simple regression analyses showed the need for proposing models with multiple inputs, which resulted in creating the three models of IWO-ANN, ABC-ANN, and ICA-ANN, among which the IWO-ANN was finally found to be more successful in solving the problem at hand compared to the other two models. The results of the new IWO-ANN models for the training and testing sections were R<sup>2</sup> = 0.928 and 0.917, respectively, which highlighted the high capabilities of this model for TS prediction. Hence, it can be used as a new solution for training intelligent systems on various issues.

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## References

1. Baykasoğlu, A.; Güllü, H.; Çanakçı, H.; Özbakır, L. Prediction of compressive and tensile strength of limestone via genetic programming. *Expert Syst. Appl.* **2008**, *35*, 111–123. [[CrossRef](#)]
2. Kahraman, S.; Fener, M.; Kozman, E. Predicting the compressive and tensile strength of rocks from indentation hardness index. *J. S. Afr. Inst. Min. Metall.* **2012**, *112*, 331–339.

3. Heidari, M.; Khanlari, G.R.; Kaveh, M.T.; Kargarian, S. Predicting the Uniaxial Compressive and Tensile Strengths of Gypsum Rock by Point Load Testing. *Rock Mech. Rock Eng.* **2012**, *45*, 265–273. [[CrossRef](#)]
4. Singh, V.; Singh, D.; Singh, T. Prediction of strength properties of some schistose rocks from petrographic properties using artificial neural networks. *Int. J. Rock Mech. Min. Sci.* **2001**, *38*, 269–284. [[CrossRef](#)]
5. Nazir, R.; Momeni, E.; Armaghani, D.J.; Amin, M.F.M. Correlation between unconfined compressive strength and indirect tensile strength of limestone rock samples. *Electron. J. Geotech. Eng.* **2013**, *18*, 1737–1746.
6. Ulusay, R.; Hudson, J.A.; ISRM. *The Complete ISRM Suggested Methods for Rock Characterization, Testing and Monitoring: 1974–2006*; Commission on Testing Methods, International Society for Rock Mechanics; ISRM Turkish Natl Group: Ankara, Turkey, 2007; 628 p.
7. Kahraman, S.; Bilgin, N.; Feridunoglu, C. Dominant rock properties affecting the penetration rate of percussive drills. *Int. J. Rock Mech. Min. Sci.* **2003**, *40*, 711–723. [[CrossRef](#)]
8. Mishra, D.A.; Basu, A. Use of the block punch test to predict the compressive and tensile strengths of rocks. *Int. J. Rock Mech. Min. Sci.* **2012**, *51*, 119–127. [[CrossRef](#)]
9. Sheorey, P.R. *Empirical Rock Failure Criteria*; A A Balkema: Rotterdam, The Netherlands, 1997.
10. Perras, M.A.; Diederichs, M.S. A Review of the Tensile Strength of Rock: Concepts and Testing. *Geotech. Geol. Eng.* **2014**, *32*, 525–546. [[CrossRef](#)]
11. Armaghani, D.J.; Amin, M.F.M.; Yagiz, S.; Faradonbeh, R.S.; Abdullah, R.A. Prediction of the uniaxial compressive strength of sandstone using various modeling techniques. *Int. J. Rock Mech. Min. Sci.* **2016**, *85*, 174–186. [[CrossRef](#)]
12. Koopialipoor, M.; Fahimifar, A.; Ghaleini, E.N.; Momenzadeh, M.; Armaghani, D.J. Development of a new hybrid ANN for solving a geotechnical problem related to tunnel boring machine performance. *Eng. Comput.* **2019**, 1–13. [[CrossRef](#)]
13. Zhou, J.; Aghili, N.; Ghaleini, E.N.; Bui, D.T.; Tahir, M.M.; Koopialipoor, M. A Monte Carlo simulation approach for effective assessment of flyrock based on intelligent system of neural network. *Eng. Comput.* **2019**, 1–11. [[CrossRef](#)]
14. Asteris, P.G.; Nozhati, S.; Nikoo, M.; Cavaleri, L.; Nikoo, M. Krill herd algorithm-based neural network in structural seismic reliability evaluation. *Mech. Adv. Mater. Struct.* **2019**, *26*, 1146–1153. [[CrossRef](#)]
15. Chahnasir, E.S.; Zandi, Y.; Shariati, M.; Dehghani, E.; Toghrol, A.; Mohamad, E.T.; Shariati, A.; Safa, M.; Wakil, K.; Khorami, M. Application of support vector machine with firefly algorithm for investigation of the factors affecting the shear strength of angle shear connectors. *SMART Struct. Syst.* **2018**, *22*, 413–424.
16. Mohammadhassani, M.; Nezamabadi-Pour, H.; Suhatri, M.; Shariati, M. Identification of a suitable ANN architecture in predicting strain in tie section of concrete deep beams. *Struct. Eng. Mech.* **2013**, *46*, 853–868. [[CrossRef](#)]
17. Toghrol, A.; Suhatri, M.; Ibrahim, Z.; Safa, M.; Shariati, M.; Shamshirband, S. Potential of soft computing approach for evaluating the factors affecting the capacity of steel–concrete composite beam. *J. Intell. Manuf.* **2018**, *29*, 1793–1801. [[CrossRef](#)]
18. Safa, M.; Shariati, M.; Ibrahim, Z.; Toghrol, A.; Baharom, S.B.; Nor, N.M.; Petkovic, D. Potential of adaptive neuro fuzzy inference system for evaluating the factors affecting steel-concrete composite beam’s shear strength. *Steel Compos. Struct.* **2016**, *21*, 679–688. [[CrossRef](#)]
19. Hasanipanah, M.; Amnieh, H.B.; Khamesi, H.; Armaghani, D.J.; Golzar, S.B.; Shahnazari, A. Prediction of an environmental issue of mine blasting: An imperialistic competitive algorithm-based fuzzy system. *Int. J. Environ. Sci. Technol.* **2018**, *15*, 551–560. [[CrossRef](#)]
20. Jiang, W.; Arslan, C.A.; Tehrani, M.S.; Khorami, M.; Hasanipanah, M. Simulating the peak particle velocity in rock blasting projects using a neuro-fuzzy inference system. *Eng. Comput.* **2019**, *35*, 1203–1211. [[CrossRef](#)]
21. Rad, H.N.; Hasanipanah, M.; Rezaei, M.; Eghlim, A.L. Developing a least squares support vector machine for estimating the blast-induced flyrock. *Eng. Comput.* **2018**, *34*, 709–717. [[CrossRef](#)]
22. Zhou, J.; Li, X.; Mitri, H.S. Classification of rockburst in underground projects: Comparison of ten supervised learning methods. *J. Comput. Civ. Eng.* **2016**, *30*, 4016003. [[CrossRef](#)]
23. Zhou, J.; Shi, X.; Du, K.; Qiu, X.; Li, X.; Mitri, H.S. Feasibility of random-forest approach for prediction of ground settlements induced by the construction of a shield-driven tunnel. *Int. J. Geomech.* **2016**, *17*, 4016129. [[CrossRef](#)]
24. Liao, X.; Khandelwal, M.; Yang, H.; Koopialipoor, M.; Murlidhar, B.R. Effects of a proper feature selection on prediction and optimization of drilling rate using intelligent techniques. *Eng. Comput.* **2019**, 1–12. [[CrossRef](#)]

25. Zhou, J.; Li, E.; Wang, M.; Chen, X.; Shi, X.; Jiang, L. Feasibility of Stochastic Gradient Boosting Approach for Evaluating Seismic Liquefaction Potential Based on SPT and CPT Case Histories. *J. Perform. Constr. Facil.* **2019**, *33*, 4019024. [[CrossRef](#)]
26. Zhou, J.; Shi, X.; Li, X. Utilizing gradient boosted machine for the prediction of damage to residential structures owing to blasting vibrations of open pit mining. *J. Vib. Control* **2016**, *22*, 3986–3997. [[CrossRef](#)]
27. Zhou, J.; Li, X.; Mitri, H.S. Evaluation method of rockburst: State-of-the-art literature review. *Tunn. Undergr. Sp. Technol.* **2018**, *81*, 632–659. [[CrossRef](#)]
28. Monjezi, M.; Dehghani, H. Evaluation of effect of blasting pattern parameters on back break using neural networks. *Int. J. Rock Mech. Min. Sci.* **2008**, *45*, 1446–1453. [[CrossRef](#)]
29. Khandelwal, M.; Armaghani, D.J.; Faradonbeh, R.S.; Ranjith, P.G.; Ghoraba, S. A new model based on gene expression programming to estimate air flow in a single rock joint. *Environ. Earth Sci.* **2016**, *75*, 739. [[CrossRef](#)]
30. Manoj, K.; Monjezi, M. Prediction of flyrock in open pit blasting operation using machine learning method. *Int. J. Min. Sci. Technol.* **2013**, *23*, 313–316. [[CrossRef](#)]
31. Khandelwal, M.; Singh, T.N. Correlating static properties of coal measures rocks with P-wave velocity. *Int. J. Coal Geol.* **2009**, *79*, 55–60. [[CrossRef](#)]
32. Harandizadeh, H.; Toufigh, M.M.; Toufigh, V. Application of improved ANFIS approaches to estimate bearing capacity of piles. *Soft Comput.* **2019**, *23*, 9537–9547. [[CrossRef](#)]
33. Asteris, P.G.; Kolovos, K.G.; Douvika, M.G.; Roinos, K. Prediction of self-compacting concrete strength using artificial neural networks. *Eur. J. Environ. Civ. Eng.* **2016**, *20*, s102–s122. [[CrossRef](#)]
34. Apostolopoulou, M.; Armaghani, D.J.; Bakolas, A.; Douvika, M.G.; Moropoulou, A.; Asteris, P.G. Compressive strength of natural hydraulic lime mortars using soft computing techniques. *Procedia Struct. Integr.* **2019**, *17*, 914–923. [[CrossRef](#)]
35. Armaghani, D.J.; Koopialipoor, M.; Marto, A.; Yagiz, S. Application of several optimization techniques for estimating TBM advance rate in granitic rocks. *J. Rock Mech. Geotech. Eng.* **2019**, *11*, 779–789. [[CrossRef](#)]
36. Xu, H.; Zhou, J.; G.Asteris, P.; Jahed Armaghani, D.; Tahir, M.M. Supervised Machine Learning Techniques to the Prediction of Tunnel Boring Machine Penetration Rate. *Appl. Sci.* **2019**, *9*, 3715. [[CrossRef](#)]
37. Armaghani, D.J.; Hatzigeorgiou, G.D.; Karamani, C.; Skentou, A.; Zoumpoulaki, I.; Asteris, P.G. Soft computing-based techniques for concrete beams shear strength. *Procedia Struct. Integr.* **2019**, *17*, 924–933. [[CrossRef](#)]
38. Asteris, P.G.; Nikoo, M. Artificial bee colony-based neural network for the prediction of the fundamental period of infilled frame structures. *Neural Comput. Appl.* **2019**, 1–11. [[CrossRef](#)]
39. Asteris, P.G.; Moropoulou, A.; Skentou, A.D.; Apostolopoulou, M.; Mohebkhah, A.; Cavaleri, L.; Rodrigues, H.; Varum, H. Stochastic Vulnerability Assessment of Masonry Structures: Concepts, Modeling and Restoration Aspects. *Appl. Sci.* **2019**, *9*, 243. [[CrossRef](#)]
40. Hajihassani, M.; Abdullah, S.S.; Asteris, P.G.; Armaghani, D.J. A Gene Expression Programming Model for Predicting Tunnel Convergence. *Appl. Sci.* **2019**, *9*, 4650. [[CrossRef](#)]
41. Asteris, P.G.; Apostolopoulou, M.; Skentou, A.D.; Moropoulou, A. Application of artificial neural networks for the prediction of the compressive strength of cement-based mortars. *Comput. Concr.* **2019**, *24*, 329–345.
42. Cavaleri, L.; Asteris, P.G.; Psyllaki, P.P.; Douvika, M.G.; Skentou, A.D.; Vaxevanidis, N.M. Prediction of Surface Treatment Effects on the Tribological Performance of Tool Steels Using Artificial Neural Networks. *Appl. Sci.* **2019**, *9*, 2788. [[CrossRef](#)]
43. Asteris, P.G.; Tsaris, A.K.; Cavaleri, L.; Repapis, C.C.; Papalou, A.; Di Trapani, F.; Karypidis, D.F. Prediction of the fundamental period of infilled RC frame structures using artificial neural networks. *Comput. Intell. Neurosci.* **2016**, *2016*, 20. [[CrossRef](#)]
44. Psyllaki, P.; Stamatou, K.; Iliadis, I.; Mourlas, A.; Asteris, P.; Vaxevanidis, N. Surface treatment of tool steels against galling failure. In MATEC Web of Conferences. *EDP Sci.* **2018**, *188*, 4024.
45. Asteris, P.G.; Ashrafian, A.; Rezaie-Balf, M. Prediction of the compressive strength of self-compacting concrete using surrogate models. *Comput. Concr.* **2019**, *24*, 137–150.
46. Koopialipoor, M.; Tootoonchi, H.; Armaghani, D.J.; Mohamad, E.T.; Hedayat, A. Application of deep neural networks in predicting the penetration rate of tunnel boring machines. *Bull. Eng. Geol. Environ.* **2019**, 1–14. [[CrossRef](#)]

47. Yang, H.Q.; Li, Z.; Jie, T.Q.; Zhang, Z.Q. Effects of joints on the cutting behavior of disc cutter running on the jointed rock mass. *Tunn. Undergr. Sp. Technol.* **2018**, *81*, 112–120. [[CrossRef](#)]
48. Yang, H.Q.; Xing, S.G.; Wang, Q.; Li, Z. Model test on the entrainment phenomenon and energy conversion mechanism of flow-like landslides. *Eng. Geol.* **2018**, *239*, 119–125. [[CrossRef](#)]
49. Yang, H.; Liu, J.; Liu, B. Investigation on the cracking character of jointed rock mass beneath TBM disc cutter. *Rock Mech. Rock Eng.* **2018**, *51*, 1263–1277. [[CrossRef](#)]
50. Zhou, J.; Koopialipoor, M.; Murlidhar, B.R.; Fatemi, S.A.; Tahir, M.M.; Armaghani, D.J.; Li, C. Use of Intelligent Methods to Design Effective Pattern Parameters of Mine Blasting to Minimize Flyrock Distance. *Nat. Resour. Res.* **2019**, 1–15. [[CrossRef](#)]
51. Guo, H.; Zhou, J.; Koopialipoor, M.; Armaghani, D.J.; Tahir, M.M. Deep neural network and whale optimization algorithm to assess flyrock induced by blasting. *Eng. Comput.* **2019**, 1–14. [[CrossRef](#)]
52. Koopialipoor, M.; Nikouei, S.S.; Marto, A.; Fahimifar, A.; Armaghani, D.J.; Mohamad, E.T. Predicting tunnel boring machine performance through a new model based on the group method of data handling. *Bull. Eng. Geol Environ.* **2018**, *78*, 3799–3813. [[CrossRef](#)]
53. Asteris, P.; Roussis, P.; Douvika, M. Feed-forward neural network prediction of the mechanical properties of sandcrete materials. *Sensors* **2017**, *17*, 1344. [[CrossRef](#)] [[PubMed](#)]
54. Cavaleri, L.; Chatzarakis, G.E.; Di Trapani, F.; Douvika, M.G.; Roinos, K.; Vaxevanidis, N.M.; Asteris, P.G. Modeling of Surface Roughness in Electro-Discharge Machining Using Artificial Neural Networks. *Adv. Mater. Res.* **2017**, *6*, 169–184.
55. Sarir, P.; Chen, J.; Asteris, P.G.; Armaghani, D.J.; Tahir, M.M. Developing GEP tree-based, neuro-swarm, and whale optimization models for evaluation of bearing capacity of concrete-filled steel tube columns. *Eng. Comput.* **2019**, 1–19. [[CrossRef](#)]
56. Chen, H.; Asteris, P.G.; Jahed Armaghani, D.; Gordan, B.; Pham, B.T. Assessing Dynamic Conditions of the Retaining Wall: Developing Two Hybrid Intelligent Models. *Appl. Sci.* **2019**, *9*, 1042. [[CrossRef](#)]
57. Kumar, B.R.; Vardhan, H.; Govindaraj, M. Prediction of Uniaxial Compressive Strength, Tensile Strength and Porosity of Sedimentary Rocks Using Sound Level Produced During Rotary Drilling. *Rock Mech. Rock Eng.* **2011**, *44*, 613–620. [[CrossRef](#)]
58. Koopialipoor, M.; Ghaleini, E.N.; Haghighi, M.; Kanagarajan, S.; Maarefvand, P.; Mohamad, E.T. Overbreak prediction and optimization in tunnel using neural network and bee colony techniques. *Eng. Comput.* **2019**, *35*, 1191–1202. [[CrossRef](#)]
59. Zhao, Y.; Noorbakhsh, A.; Koopialipoor, M.; Azizi, A.; Tahir, M.M. A new methodology for optimization and prediction of rate of penetration during drilling operations. *Eng. Comput.* **2019**, 1–9. [[CrossRef](#)]
60. Koopialipoor, M.; Fallah, A.; Armaghani, D.J.; Azizi, A.; Mohamad, E.T. Three hybrid intelligent models in estimating flyrock distance resulting from blasting. *Eng. Comput.* **2019**, *35*, 243–256. [[CrossRef](#)]
61. Ghaleini, E.N.; Koopialipoor, M.; Momenzadeh, M.; Sarafraz, M.E.; Mohamad, E.T.; Gordan, B. A combination of artificial bee colony and neural network for approximating the safety factor of retaining walls. *Eng. Comput.* **2018**, *35*, 647–658. [[CrossRef](#)]
62. Koopialipoor, M.; Armaghani, D.J.; Hedayat, A.; Marto, A.; Gordan, B. Applying various hybrid intelligent systems to evaluate and predict slope stability under static and dynamic conditions. *Soft Comput.* **2019**, *23*, 5913–5929. [[CrossRef](#)]
63. Koopialipoor, M.; Armaghani, D.J.; Haghighi, M.; Ghaleini, E.N. A neuro-genetic predictive model to approximate overbreak induced by drilling and blasting operation in tunnels. *Bull. Eng. Geol Environ.* **2019**, *78*, 981–990. [[CrossRef](#)]
64. Mohamad, E.T.; Armaghani, D.J.; Momeni, E.; Yazdavar, A.H.; Ebrahimi, M. Rock strength estimation: A PSO-based BP approach. *Neural Comput. Appl.* **2018**, *30*, 1635–1646. [[CrossRef](#)]
65. Atashpaz-Gargari, E.; Lucas, C. Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition. In Proceedings of the IEEE Congress on Evolutionary Computation (CEC 2007), Singapore, 25–28 September 2007; pp. 4661–4667.
66. Hajihassani, M.; Jahed Armaghani, D.; Marto, A.; Tonnizam Mohamad, E. Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. *Bull. Eng. Geol Environ.* **2014**, *74*, 873–886. [[CrossRef](#)]
67. Armaghani, D.J.; Hasanipanah, M.; Mohamad, E.T. A combination of the ICA-ANN model to predict air-overpressure resulting from blasting. *Eng. Comput.* **2016**, *32*, 155–171. [[CrossRef](#)]

68. Gordan, B.; Koopialipoor, M.; Clementking, A.; Tootoonchi, H.; Mohamad, E.T. Estimating and optimizing safety factors of retaining wall through neural network and bee colony techniques. *Eng Comput.* **2019**, *35*, 945–954. [[CrossRef](#)]
69. Armaghani, D.J.; Mohamad, E.T.; Narayanasamy, M.S.; Narita, N.; Yagiz, S. Development of hybrid intelligent models for predicting TBM penetration rate in hard rock condition. *Tunn. Undergr. Sp. Technol.* **2017**, *63*, 29–43. [[CrossRef](#)]
70. Karaboga, D. *An Idea Based on Honey Bee Swarm for Numerical Optimization*; Technical Report-tr06; Erciyes University, Engineering Faculty, Computer Engineering Department: Kayseri, Turkey, 2005.
71. Nozohour-leilabady, B.; Fazelabdolabadi, B. On the application of artificial bee colony (ABC) algorithm for optimization of well placements in fractured reservoirs; efficiency comparison with the particle swarm optimization (PSO) methodology. *Petroleum* **2016**, *2*, 79–89. [[CrossRef](#)]
72. Ahmad, A.; Razali, S.F.M.; Mohamed, Z.S.; El-shafie, A. The Application of Artificial Bee Colony and Gravitational Search Algorithm in Reservoir Optimization. *Water Resour. Manag.* **2016**, *30*, 2497–2516. [[CrossRef](#)]
73. Zhang, C.; Ouyang, D.; Ning, J. An artificial bee colony approach for clustering. *Expert Syst. Appl.* **2010**, *37*, 4761–4767. [[CrossRef](#)]
74. Rodriguez, F.J.; García-Martínez, C.; Blum, C.; Lozano, M. An artificial bee colony algorithm for the unrelated parallel machines scheduling problem. In *International Conference on Parallel Problem Solving from Nature*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 143–152.
75. Oliveira, I.M.S.D.; Schirru, R.; de Medeiros, J. On the performance of an artificial bee colony optimization algorithm applied to the accident diagnosis in a pwr nuclear power plant. In *Proceedings of the 2009 international nuclear Atlantic conference (INAC 2009)*, Rio de Janeiro, Brazil, 27 September–2 October 2009.
76. Irani, R.; Nasimi, R. Application of artificial bee colony-based neural network in bottom hole pressure prediction in underbalanced drilling. *J. Pet. Sci. Eng.* **2011**, *78*, 6–12. [[CrossRef](#)]
77. Ebrahimi, E.; Monjezi, M.; Khalesi, M.R.; Armaghani, D.J. Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bull. Eng. Geol. Environ.* **2016**, *75*, 27–36. [[CrossRef](#)]
78. Karaboga, D.; Basturk, B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony (ABC) algorithm. *J. Glob. Optim.* **2007**, *39*, 459–471. [[CrossRef](#)]
79. Sun, L.; Koopialipoor, M.; Armaghani, D.J.; Tarinejad, R.; Tahir, M.M. Applying a meta-heuristic algorithm to predict and optimize compressive strength of concrete samples. *Eng. Comput.* **2019**, 1–13. [[CrossRef](#)]
80. Koopialipoor, M.; Ghaleini, E.N.; Tootoonchi, H.; Armaghani, D.J.; Haghghi, M.; Hedayat, A. Developing a new intelligent technique to predict overbreak in tunnels using an artificial bee colony-based ANN. *Environ. Earth Sci.* **2019**, *78*, 165. [[CrossRef](#)]
81. Mehrabian, A.R.; Lucas, C. A novel numerical optimization algorithm inspired from weed colonization. *Ecol. Inform.* **2006**, *1*, 355–366. [[CrossRef](#)]
82. Bashir, Z.A.; El-Hawary, M.E. Applying wavelets to short-term load forecasting using PSO-based neural networks. *IEEE Trans. Power Syst.* **2009**, *24*, 20–27. [[CrossRef](#)]
83. Lin, C.-J.; Hsieh, M.-H. Classification of mental task from EEG data using neural networks based on particle swarm optimization. *Neurocomputing* **2009**, *72*, 1121–1130. [[CrossRef](#)]
84. Taghavifar, H.; Mardani, A.; Taghavifar, L. A hybridized artificial neural network and imperialist competitive algorithm optimization approach for prediction of soil compaction in soil bin facility. *Measurement* **2013**, *46*, 2288–2299. [[CrossRef](#)]
85. Yagiz, S.; Karahan, H. Prediction of hard rock TBM penetration rate using particle swarm optimization. *Int. J. Rock Mech. Min. Sci.* **2011**, *48*, 427–433. [[CrossRef](#)]
86. Armaghani, D.J.; Hasanipanah, M.; Mahdiyar, A.; Majid, M.Z.A.; Amnieh, H.B.; Tahir, M.M. Airblast prediction through a hybrid genetic algorithm-ANN model. *Neural Comput. Appl.* **2018**, *29*, 619–629. [[CrossRef](#)]
87. Momeni, E.; Nazir, R.; Armaghani, D.J.; Maizir, H. Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN. *Measurement* **2014**, *57*, 122–131. [[CrossRef](#)]
88. Liou, S.-W.; Wang, C.-M.; Huang, Y.-F. Integrative Discovery of Multifaceted Sequence Patterns by Frame-Relayed Search and Hybrid PSO-ANN. *J. UCS* **2009**, *15*, 742–764.

89. Asteris, P.G.; Armaghani, D.J.; Hatzigeorgiou, G.D.; Karayannis, C.G.; Pilakoutas, K. Predicting the shear strength of reinforced concrete beams using Artificial Neural Networks. *Comput. Concr.* **2019**, *24*, 469–488.
90. Asteris, P.G.; Kolovos, K.G. Self-compacting concrete strength prediction using surrogate models. *Neural Comput. Appl.* **2019**, *31*, 409–424. [[CrossRef](#)]
91. Armaghani, D.; Mohamad, E.; Hajihassani, M. Evaluation and prediction of flyrock resulting from blasting operations using empirical and computational methods. *Eng. Comput.* **2016**, *32*, 109–121. [[CrossRef](#)]
92. Hornik, K.; Stinchcombe, M.; White, H. Multilayer feedforward networks are universal approximators. *Neural Netw.* **1989**, *2*, 359–366. [[CrossRef](#)]
93. Mohamad, E.T.; Faradonbeh, R.S.; Armaghani, D.J.; Monjezi, M.; Majid, M.Z.A. An optimized ANN model based on genetic algorithm for predicting ripping production. *Neural Comput. Appl.* **2017**, *28*, 393–406. [[CrossRef](#)]
94. Armaghani, D.J.; Hajihassani, M.; Sohaei, H.; Mohamad, E.T.; Marto, A.; Motaghedi, H.; Moghaddam, M.R. Neuro-fuzzy technique to predict air-overpressure induced by blasting. *Arab. J. Geosci.* **2015**, *8*, 10937–10950. [[CrossRef](#)]
95. Sonmez, H.; Gokceoglu, C.; Nefeslioglu, H.A.; Kayabasi, A. Estimation of rock modulus: For intact rocks with an artificial neural network and for rock masses with a new empirical equation. *Int. J. Rock Mech. Min. Sci.* **2006**, *43*, 224–235. [[CrossRef](#)]
96. Yang, H.; Koopialipoor, M.; Armaghani, D.J.; Gordan, B.; Khorami, M.; Tahir, M.M. Intelligent design of retaining wall structures under dynamic conditions. *Steel Compos. Struct.* **2019**, *31*, 629–640.
97. Koopialipoor, M.; Noorbakhsh, A.; Noroozi Ghaleini, E.; Jahed Armaghani, D.; Yagiz, S. A new approach for estimation of rock brittleness based on non-destructive tests. *Nondestruct. Test. Eval.* **2019**, 1–22. [[CrossRef](#)]
98. Xu, C.; Gordan, B.; Koopialipoor, M.; Armaghani, D.J.; Tahir, M.M.; Zhang, X. Improving Performance of Retaining Walls Under Dynamic Conditions Developing an Optimized ANN Based on Ant Colony Optimization Technique. *IEEE Access* **2019**, *7*, 94692–94700. [[CrossRef](#)]
99. Mohamad, E.T.; Koopialipoor, M.; Murlidhar, B.R.; Rashiddel, A.; Hedayat, A.; Armaghani, D.J. A new hybrid method for predicting ripping production in different weathering zones through in-situ tests. *Measurement* **2019**, *147*, 106826. [[CrossRef](#)]
100. Koopialipoor, M.; Murlidhar, B.R.; Hedayat, A.; Armaghani, D.J.; Gordan, B.; Mohamad, E.T. The use of new intelligent techniques in designing retaining walls. *Eng. Comput.* **2019**, 1–2. [[CrossRef](#)]
101. Zorlu, K.; Gokceoglu, C.; Ocakoglu, F.; Nefeslioglu, H.A.; Acikalin, S. Prediction of uniaxial compressive strength of sandstones using petrography-based models. *Eng. Geol.* **2008**, *96*, 141–158. [[CrossRef](#)]



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