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A precise neuro-fuzzy model enhanced by artificial bee colony techniques for assessment of rock brittleness index

Maryam Parsajoo[1] · Danial Jahed Armaghani[2] · Panagiotis G. Asteris[3]

Abstract

When planning rock-based projects, the brittleness index (BI) may play a significant role in the success of various projects, such as tunnel boring machines and road headers. Lack of accurate BI prediction of the rock sample may result in numerous disastrous incidents associated with rock mechanics. Adaptive neuro-fuzzy inference system (ANFIS) is a model for predicting the rock's BI. However, the performance of this model mainly depends on its parameter values and tuning these values requires knowledge and time. This study improves the performance of ANFIS modeling using an Artificial Bee Colony (ABC) optimization algorithm to automatically optimize the parameters of ANFIS, called ANFIS_ABC. Three versions of ANFIS_ABC algorithms were proposed to predict the BI of rock, in which the ABC algorithm was applied in different model development stages. The performance of the proposed predictive models was evaluated using the rock samples collected from a tunneling project in Malaysia comprising 113 samples. The Schmidt hammer rebound number (Rn) (ranging from 20 to 61), P-wave velocity (Vp) (ranging from 2870 to 7702 m/s), and Point load index (IS_{50}) (ranging from 0.89 to 7.1 MPa) were used as input parameters. According to the results obtained by the various performance indices, the proposed model (i.e., ANFIS_ABC_PC) was able to receive the highest accuracy level in predicting rock BI among all constructed models. The developed model may be applied with caution to relevant areas of rock mechanics.

Keywords Adaptive Neuro-Fuzzy Inference System (ANFIS) · Artificial Bee Colony (ABC) · Brittleness index · Optimized ANFIS-based model

Abbreviations

ANFIS	Adaptive neuro-fuzzy inference system
UCS	Uniaxial compressive strength
TBM	Tunnel boring machine
Gbell	Generalized Bell
ANN	Artificial neural network
TS	Tensile strength
AI	Artificial intelligence
ML	Machine learning
PSO	Particle swarm optimization
ABC	Artificial bee colony
BI	Brittleness index
FA	Firefly algorithm
DE	Differential evolution
GA	Genetic algorithm
ICA	Imperialism competitive algorithm
Ω	Inertia weight
FIS	Fuzzy inference system
c_1 and c_2	Acceleration coefficients
ACO	Ant colony optimization
R_n	Schmidt hammer rebound number
RMSE	Root mean square error
V_p	P-wave velocity
Is_{50}	Point load index
R^2	Coefficient of determination
MAE	Mean absolute error

✉ Danial Jahed Armaghani
danialarmaghani@susu.ru

Maryam Parsajoo
Maryam.parsajoo@shamsdc.com

Panagiotis G. Asteris
asteris@aspete.gr; panagiotisasteris@gmail.com

[1] Department of Mining Engineering, Shams Co, no. 1380. way no. 2818, Postal Code 114, Shatti Al Qurum, P.O.Box 1941, Muscat, Sultanate of Oman

[2] Department of Urban Planning, Engineering Networks and Systems, Institute of Architecture and Construction, South Ural State University, 76, Lenin Prospect, Chelyabinsk 454080, Russia

[3] Computational Mechanics Laboratory, School of Pedagogical and Technological Education, 14121 HeraklionAthens, GR, Greece

SI   Scatter index
VAF   Variance account for
SVM   Support vector machine
FS   Feature selection
BTS   Brazilian tensile strength

1 Introduction

The brittleness of rock, which may defined as the ratio of Uniaxial Compressive Strength (UCS) to Tensile Strength (TS) [1], is a key property of rock mass that should be considered in all excavation and tunneling projects. In addition, it is considered an important property in different civil and mining work applications. For example, an in depth understanding of rock brittleness is critical in the areas of oil and gas projects. This may assist in the evaluation of the performance and stability of possible hydraulic failures. Moreover, the brittleness index (BI) can control mechanical characteristics of the rocks. It is important to note that the rock strength can be calculated by the volumetric fraction of weak constituents, strong minerals, and carbonates [2]. Rocks with a higher brittleness index can break easily at small strains.

Different studies introduced empirical and computational techniques to determine rock brittleness [3–9]. The empirical approaches are usually based on the tensile and compressive strength, and the applied proposals are based on different relationships of TS and UCS [10, 11]. However, there are some additional parameters such as the Poisson's ratio, rock density, plastic strain, applied load at failure, penetration depth at the maximum force, and elastic modulus in other published empirical equations [4, 12–14]. It is important to mention that the widely-used empirical relationship used to calculate the BI calculates the ratio of compression strength values to tensile strength values [15]. Tensile and compression strengths are often assessed using the Brazilian tensile strength (BTS) and UCS tests, respectively. When calculating the BI using these tests, the computation is overwhelmingly expensive and time-consuming [6]. In addition, sample preparation for these tests based on the available guidelines, is a difficult task as mentioned by many researchers [16, 17]. Therefore, the use of rock index tests for BI prediction is of importance. In addition to tensile and compression strengths, other characteristics, such as frictional strength, rock density, elasticity modulus, are used for formulating different heuristics in order to predict BI in different conditions and rock types [11]. Although these heuristics processes or methods can be used for predicting BI, developing more computational techniques with higher degree of accuracy is required to solve rock BI problem.

It has been proved that strength-based approaches (e.g., UCS or TS) cannot be efficient in characterizing rock brittleness [18, 19]. To address this weakness, some techniques have been developed during past decades. For example, punch penetration tests were used by Yagiz [4] to derive rock BI. In another research carried out by Guo and Chapman [20], the brittleness of shale rocks was assessed by employing a non-strength-based rock physics template. Tarasov and Potvin [21] used the aggregated elastic energy and rupture energy as two important parameters to obtain rock fragility properties under different loading conditions. Rock brittleness was used for estimating the performance of tunnel boring machine (TBM) as reported by Yagiz et al. [22] and Yagiz and Karahan [23]. They mentioned that BI is one of the important factors influencing TBM performance. One of the major shortcomings of strength-based approaches is that they do not consider the effect of elastic strain and confining stress. These two parameters are necessary for determining the amount of applied energy during loading and before failure occurs [24]. On the other hand, the majority of conventional models use one or two dependent parameters, which fail to estimate BI values with sufficient accuracy [25, 26]. The use of artificial intelligence (AI), machine learning (ML), and evolutionary computing techniques in solving problems in science and engineering has been highlighted in many studies [27–44] and specifically in estimating BI values [1, 5, 6, 15, 25, 26]. Unlike regression analysis techniques, AI and ML techniques do not force the predicted BI value to be a mean value; thus, they can maintain the variance of the measured data. Recently, artificial neural network (ANN) were employed for the prediction of rock brittleness [18]. A fuzzy inference system (FIS) was designed for the prediction of BI as reported by Yagiz and Gokceoglu [25]. Koopialipoor et al. [1] integrated a firefly algorithm (FA) into an ANN algorithm for the prediction of BI values of rock. Different intact rock properties, such as the p-wave velocity and density, were considered in the development of the model. Hussain et al. [2] optimized the weights of the equations predicting the BI by employing a swarm-based optimization algorithm, i.e., particle swarm optimization (PSO). It is important to note that AI and ML models have been used and introduced to solve civil and mining problems [27, 45–54].

Strength-based techniques can be used as indirect tools to measure/predict the brittleness of rock. Indirect use of BTS, UCS, and fragment size distribution is considered as a useful technique in assessing the performance of mechanical drilling in tunneling. However, strength-based approaches cannot evaluate the rock brittleness under

various loading conditions. Existing systems may sometimes be inconsistent with each other or may depend on specific test and measurement conditions, resulting in limited use. On the other hand, a system that can determine rock brittleness under a broad scope of ductility is not available [24]. This research investigates the application of an adaptive neuro-fuzzy inference system (ANFIS) algorithm, which combines the learning ability of both neural networks and FIS. ANFIS has been utilized in the context of various prediction purposes. The parameters used in ANFIS are enhanced using an optimization algorithm applied during training stages [55]. Derivative-based and metaheuristics-based types of algorithms have been used in the context of ANFIS training [56, 57]. Although ANFIS are efficient tools for engineering problems solving, it suffers from certain shortcomings, such as slow learning rates and entrapments in local minima [58]. These shortcomings are associated with inappropriate parameter settings of ANFIS. To address these challenges, an ANFIS system is enhanced using an artificial bee colony (ABC) algorithm with the aim of automatically tuning the parameter values. An ABC algorithm is employed over different types of parameters and three versions of improved ANFIS are proposed. The performance of the proposed algorithms is evaluated using samples collected from a tunneling site in Malaysia for the prediction of BI rock.

The paper is structured as follows: Sect. 2 presents fundamental concepts of ANFIS and ABC algorithms. Section 3 presents the database compiled in this paper. Section 4 presents a hybrid evolutionary ANFIS algorithm developed by employing the ABC approach in the parameter adjusting step of ANFIS with the aim of improving the performance of a pre-developed ANFIS model. Section 5 evaluates the proposed algorithm based on different performance indices (PIs) and discusses the results. Finally, a summary of the paper is provided in Sect. 6.

2 Methods and material

2.1 ANFIS background

An ANFIS structure consists of the premise (antecedent) and the consequence (conclusion) parts. In an ANFIS, a network model is trained by optimizing the parameters associated with these two parts. ANFIS is trained using input–output data sets. Then, IF–THEN rules, which connect two parts, are generated. Figure 1 shows a five-layer ANFIS algorithm (1) fuzzification layer, (2) rule layer, (3) normalization layer, (4) defuzzification layer, and (5) summation layer [27].

2.1.1 Layer 1: fuzzification layer

In the fuzzification layer, fuzzy clusters are obtained from input values using membership functions (MFs). The fuzzification layer is responsible for forming membership functions using parameters in the antecedent part, i.e., {a, b, c}. Indeed, these parameters determine the degrees of each MF, as expressed in Eqs. 1 and 2.

$$\mu_{A_i} = gbellmf(x; a, b, c) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \tag{1}$$

$$O_i^1 = \mu_{A_i}(x) \tag{2}$$

2.1.2 Layer 2: rule layer

In this layer, weights (w_i) for the rules are created through MFs calculated in the first layer. The weights are generated by multiplying the MFs (Eq. 3).

$$O_i^2 = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \quad i = 1, 2 \tag{3}$$

2.1.3 Layer 3: normalization layer

In this layer, normalized weights of each rule are calculated. The normalized weight is the percentage of the firing strength of a rule to the total of all firing strengths (Eq. 4):

$$O_i^3 = \underline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \tag{4}$$

2.1.4 Layer 4: defuzzification layer

In this layer, weights of the rules in each node are computed using the first order polynomial (Eq. 5).

$$O_i^4 = \underline{w_i} f_i = \underline{w_i}(p_i x. q_i x + r_i) \tag{5}$$

In this equation, w_i is the output of the third layer and the three parameters of $p_i, q_i, and\ r_i$ are conclusion parameters (i.e., the parameters that are in the consequence part). As a rule of thumb, the number of parameters in the consequence part for each rule is one more than the number of input(s).

2.1.5 Layer 5: summation layer

The predicted value in the last layer is obtained by the accumulation of all outputs obtained for each rule in the fourth layer (Eq. 6).

$$O_i^5 = overall\ output = \sum_i \overline{w_i} f_i = \frac{\sum_i \overline{w_i} f_i}{\sum_i W_i} \tag{6}$$
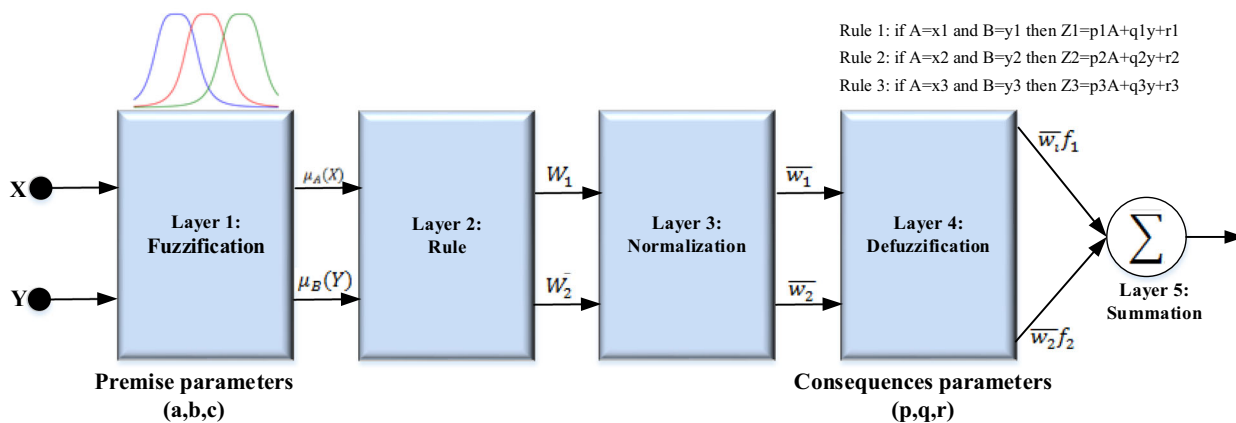
Fig. 1 Schematic of the five-layer architecture of ANFIS

2.2 Artificial Bee Colony

ABC was introduced in 2005 by Karaboga [59] and simulates the foraging characteristic of honey bees [60]. There are three groups of bees in a colony: employed, onlooker, and scout. Employed bees occupy half of the hive, and onlooker bees occupy another half of the hive. It is worth mentioning that for each food source, there is only one employed bee [61]. A scout bee is considered an employed bee type when the bee abandons a food source. Figure 2 shows a graphical representation of the ABC algorithm.

As the first step, initial food sources are generated randomly using Eq. (7). The number of food sources is a user-defined value.

$$X_{i,j} = X_{\min,j} + rand(0,1)\big(X_{\max,j} - X_{\min,j}\big) \\ i = 1, 2, \ldots, SN, \ j = 1, 2, \ldots D \tag{7}$$

where SN and D are the population size and the size of solutions, respectively, *and* (0, 1) is a function that

Fig. 2 The elements of ABC algorithm

generates a random value between 0 and 1. The notations of $X_{\min,j}$ and $X_{\max,j}$ are the lowest and highest values of the bit j, respectively.

Each solution in the bee population, is a D size vector, which represents the number of variables for a given problem. In the employed bee step, the solution is modified using Eq. (8). The amount of nectar of the new food source is then computed. If the value of the new solution is greater than the previous one, the employed bee memorizes the position of the new solution and moves to the new bee.

$$V_{i,j} = X_{i,j} + \theta_{i,j}\big(X_{i,j} - X_{i,k}\big) \tag{8}$$

In this equation, $\theta_{i,j}$ is a random value between −1 and 1, j is a randomly produced integer value between 1 and D. V_i, X_i and X_k are the new, current and the neighboring individuals, respectively. Values i and k are the indices of the food sources.

The onlooker bees perform a probabilistic selection process by considering the amount of nectar and the food sources computed by the employed bees [62]. The ith solution, P_i, is calculated as follows:

$$P_i = \frac{f_i}{\sum_{n=1}^{SN} f_n} \tag{9}$$

where, value f_i is the amount of nectar of the individual i. The computed value P_i is compared with a random value, in the range of 0 to 1. An onlooker bee goes to the region located at the X_i food source with the aim of determining a new neighboring food source. After reaching the onlooker bees in the neighborhood, each bee finds a new neighboring bee using Eq. (8) and the new solution is generated through a heuristic link between the new individual and the individual selected. In this step, a termination criterion is applied in such a way that an employed bee is converted to a scout bee and starts to explore new individuals based on a random search if the quality of an individual cannot increase after a given number of cycles (i.e., "*limit*").
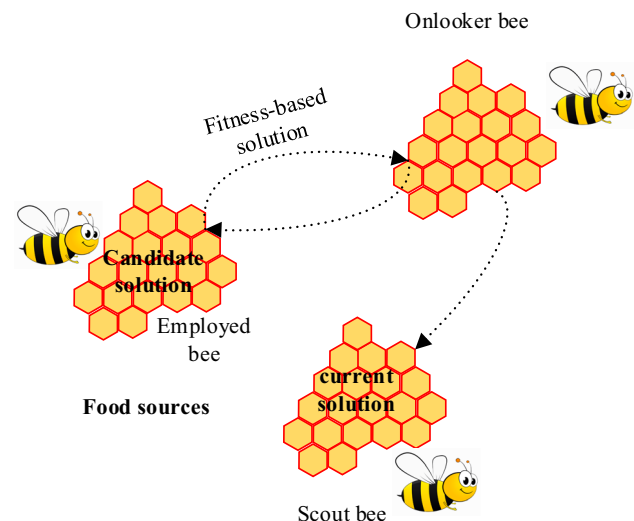
2.3 ANFIS_ABC

There are two types of parameters in the structure of ANFIS: antecedent and conclusion, which are shown in the second and forth layers of Fig. 1, respectively. Optimization algorithms can be used in two ways: in the first case, all the parameters of the two parts can be adjusted using one optimization algorithm. In the second case, two different optimization algorithms can be employed, one algorithm for the premise and another for the consequence part. This research used the first case methodology, and all parameters are optimized using the ABC algorithm.

When using evolutionary computation algorithms in ANFIS, a considerable skill and experience is required in defining the parameters of the optimization algorithm (such as population size, crossover and mutation rates, and inertia weight). The convergence speed of an evolutionary-based ANFIS model, is associated with the metaheuristic-dependent parameters. Some parameters (e.g., population size) are common in the most evolutionary computation algorithms. For example, the number of available moves is limited in Differential Evolution (DE) algorithm when the population size is too small. On the other hand, many functions that call on nearly random explorative moves can be wasted if the population size is very large. In addition to common parameters, some evolutionary techniques include their own specific parameters. For example, crossover probability and mutation probability are two parameters in genetic algorithm (GA) that need to be designed [63]. As another example, three key parameters that mainly affect convergence and efficiency of the PSO algorithms are the inertia weight (ω) and the acceleration coefficients (c_1 and c_2). Overall, the parameters of evolutionary approaches introduce different challenges to the search process such as inappropriate exploration and exploration, slow convergence, and trapping into the local minima [64].

Unlike the most well-known evolutionary algorithms such as PSO, DE, and colony optimization (ACO), imperialism competitive algorithm (ICA), FA, and GA require different control parameters, whereas the *limit* is the only control parameter in an ABC algorithm. In most of the cases, the population size and the maximum required iterations are two parameters to be set by the users or researchers. In addition to being parameter-less, an ABC algorithm can provide a balance between local exploitation and global exploration [65]. These two characteristics are important in any robust search process that should be considered together. In ABC, the exploitation process is performed by using onlooker and employed bees while the exploration process is carried out through the scout bees [65].

An ABC is integrated into ANFIS algorithm to optimize the parameters of ANFIS. Figure 3 presents the proposed ANFIS-based ABC model for the prediction of the BI of rock. ABC is employed to tune the parameters of both premise and consequence parts. ABC_ANFIS algorithm consists of two main stages. Target and independent features are determined in the preprocessing step, while ABC algorithm is applied in the second step to optimize the parameters values. The database used in this research includes four input parameters: the Schmidt hammer rebound number (R_n), p-wave velocity (V_p), point load index (Is_{50}), and the BI as the output parameter. The first three attributes are independent while the last feature is considered a target variable.

In an ABC_ANFIS algorithm, all premise and consequence parameters are associated with the individuals in the ABC algorithm. Therefore, the ABC approach is performed to find the best premise and consequence parameters in the search space. A representation of the food source position is given in Fig. 4.

In order to compute the quality of individuals, Root Mean Square Error (RMSE) is used as the fitness function. To calculate RMSE, the predicted values and its real values should be considered and used as given in Eq. 10:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(y_i - \underline{y}_i\right)}{N}} \qquad (10)$$

In this equation, y_i refers to the predicted BI values, $\underline{y}_i$ is the actual BI values and N is the size of the dataset (i.e., data sample number).

2.4 Established database

In this study, the data obtained from a tunneling project in Pahang state, Malaysia were used. This project was developed with the aim of transferring water between two states (i.e., Pahang and Selangor) in Malaysia. The excavated tunnel is 44.6 km long and has a 5.2 m diameter. The first 35 km of the tunnel were excavated by means of three TBMs, while the remaining tunnel was delved by the drilling and blasting mechanisms. In the lower half of the downstream of the tunnel, several quartz veins were found [66]. Rock sampling for the experiments was performed by conducting geotechnical research in the tunnel, and a total of 145 block rock samples were gathered from different locations of the tunnel. A series of laboratory tests were performed to correlate with the BI of the rock. The results show that R_n ranged from 20 to 61, V_p ranged from 2870 to 7702 m/s, and Is_{50} ranged from 0.89 to 7.1 MPa. Therefore, after sample preparation for each parameter, p-wave, point load, BTS, UCS, and Schmidt hammer tests were conducted on the samples in accordance with international
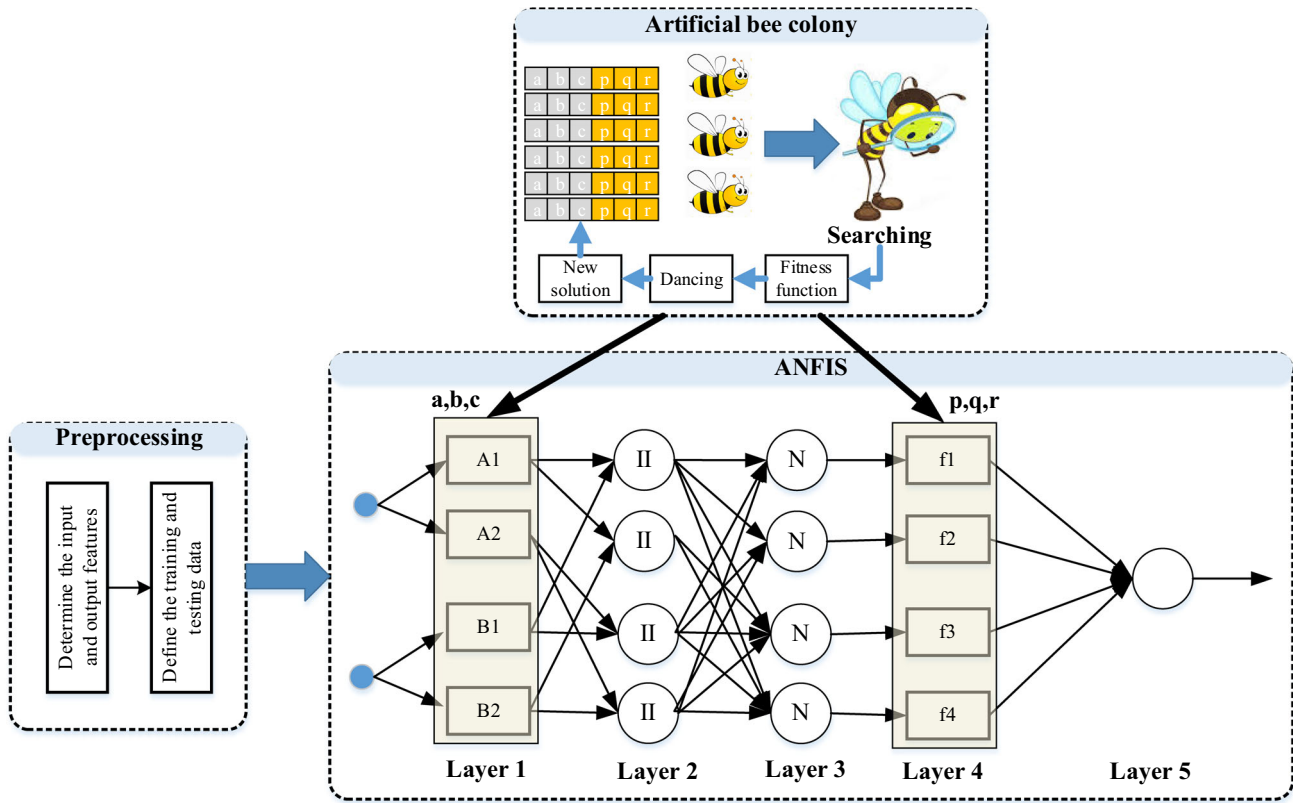
Fig. 3 The framework of ABC_ANFIS method used in this study to predict the rock BI

Fig. 4 Individual representation

society for rock mechanics guidelines [67]. It is important to mention that all BI results were calculated by dividing the UCS with BTS. Minimum, maximum, and average BI values of 8.90, 24.01, and 15.51, were obtained in order to be used in the advanced data modeling part of this research. In this study, after conducting sample preparation and the mentioned tests, a number of 113 data rows were provided to evaluate further the behavior of BI values using some rock index tests.

2.5 Evaluation measures

Different measures and performance indexes (PIs), including RMSE, Mean Absolute Error (MAE), coefficient of determination (R^2), and scatter index (SI), were utilized to evaluate the prediction performance of the proposed models [68, 69]. The equations of these PIs are presented below:

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \qquad (12)$$

$$SI = \frac{\sqrt{RSME}}{y_i} \qquad (13)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i'| \qquad (14)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(y_i - y_{mean})^2\right] - \left[\sum_{i=1}^{n}(y_i - y_i')^2\right]}{\left[\sum_{i=1}^{n}(y_i - y_{mean})^2\right]} \qquad (15)$$

In the above-mentioned equations, n, y, and y' are the number of samples, actual BI values, and predicted BI values, respectively.

2.6 Research methodology

The research methodology can be divided into four essential steps: problem definition, initial analysis, proposed method, and analysis, as depicted in Fig. 5.

The research area is to predict BI values using AI techniques. The BI prediction problem was formulated using ANFIS, which is a new research area in civil engineering. The ANFIS model has shown a high performance
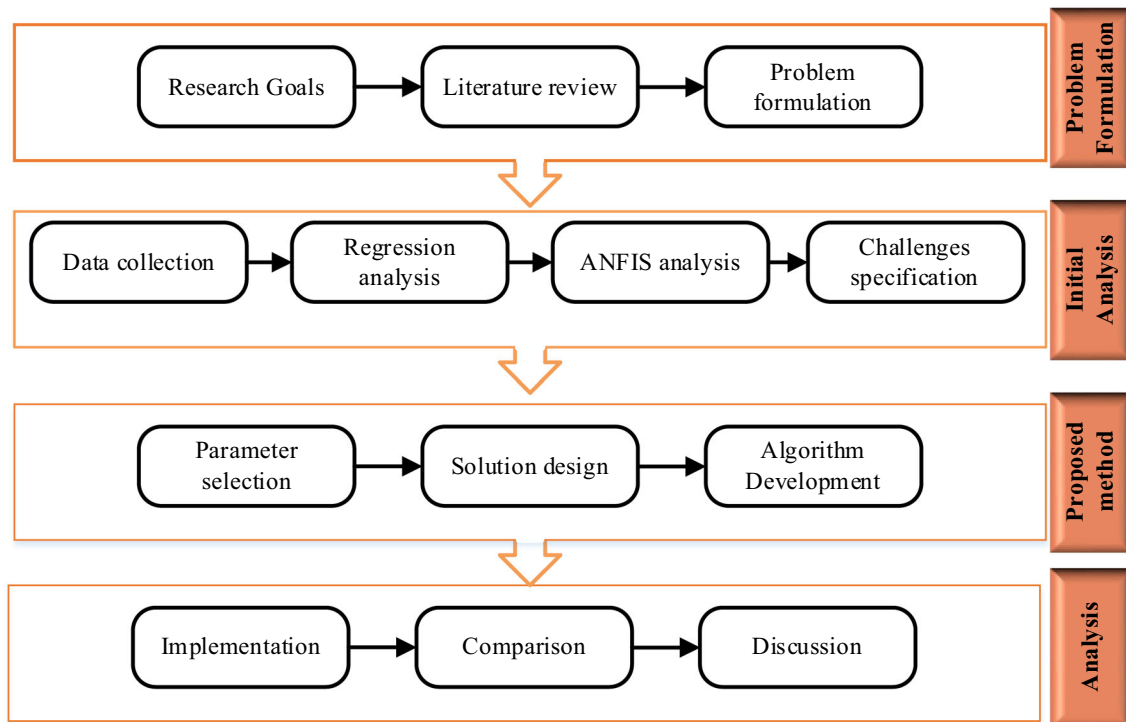
Fig. 5 Research methodology steps used in this study

in other domains of tunneling and rock mechanics [58, 70]. However, BI prediction using ANFIS needs improvement.

At the second stage, a series of rock block samples were collected from the tunneling site. Then, the relevant tests were carried out on the samples and the BI was measured in laboratory. Then, four different regression analyses, including linear, exponential, power, and logarithmic, were applied to estimate BI of the rock, empirically. To show that AI techniques have a higher prediction accuracy compared to regression analysis, an ANFIS-based BI prediction model was applied. The results show that the ANFIS algorithm is sensitive to parameters determined by the user and the prediction cannot be reliable because performance mainly depends on the expert knowledge.

In the third phase, an improved ANFIS system using ABC algorithm was developed to automatically tune the parameters of ANFIS in both the first and the fourth layers. This algorithm requires three variables and defines their MFs and the parameters of the rule weight computation. A solution was designed according to these parameters to improve the quality of solutions using ABC algorithm.

The final step includes the implementation of ANFIS_ABC algorithm and its two other versions using python language in anaconda framework. The results obtained by ANFIS_ABC were compared with the results of ANFIS algorithm as well as two versions of ANFIS_ABC in predicting rock BI.
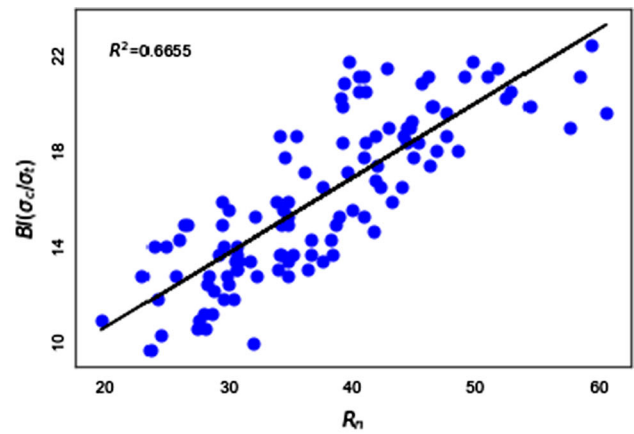
3 Regression analysis

In this section, the weights of the input parameters for the estimation of the BI of rock were examined using regression analysis. The results of the regression analysis were analyzed to establish correlations between the input variables and the BI of rock. Therefore, the physical relationships between each predictor or input parameter and model output (i.e., BI) were evaluated and discussed. In this context, four types of regressions analysis, including linear, exponential, power, and logarithmic were applied for the prediction of the BI of rock. The results are presented in Table 1, where R^2 values were used for estimating the correlations. As it is clear from this table and presented equations that all predictors or rock index tests have direct relations with the model output or rock BI. R_n is actually an indicator related to the surface hardness of rock samples which categorizes as non-destructive index test. V_p is also considered as another non-destructive index test which is able to estimate the state of compactness of the rock samples. Lastly, Is_{50} which is a destructive test, is an indicator for strength classification of rock samples and it can be easily done in both field and laboratory. The entire used non-destructive and destructive index tests are related to the strength of rock samples, and on the other hand, BI should be calculated by dividing two important indices (UCS/BTS). Therefore, since the nature of all parameters

**Table 1** Proposed BI equations using Is_{50}, R_n, and V_p

Regression model	Predictor	Regression function	R^2
Linear	V_p	BI = 0.001 V$_p$ + 7.4347	0.5648
	R_n	BI = 0.111 R$_n$ + 8.4403	0.6655
	Is_{50}	BI = 14.693*(Is$_{50}$) − 24.692	0.5697
Exponential	V_p	BI = $8.3356.e^{8E-05*V_p}$	0.5648
	R_n	BI = $9.0322.e^{0.0087*R_n}$	0.6655
	Is_{50}	BI = $0.6386.e^{1.1725*Is_{50}}$	0.5718
Power	V_p	$0.5318 * V_p^{0.3715}$	0.5434
	R_n	$4.123 * R_n^{0.3094}$	0.6578
	Is_{50}	$0.8023 * Is_{50}^{2.9513}$	0.5556
Logarithmic	V_p	BI = $4.6927.\ln(V_p) − 27.304$	0.5276
	R_n	BI = $3.9137.\ln(R_n) − 1.4481$	0.6497
	Is_{50}	BI = $36.955.\ln(Is_{50}) − 21.804$	0.5233
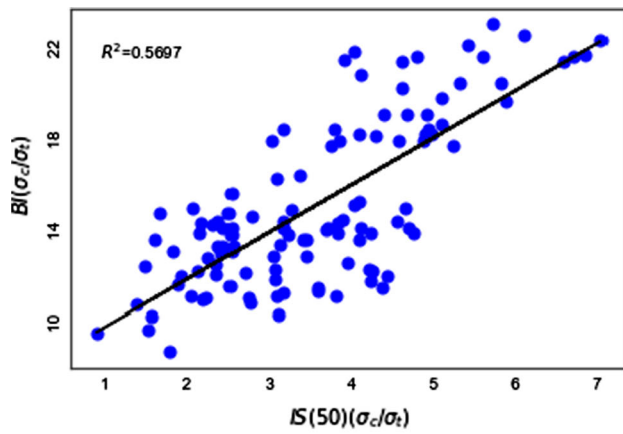
(a) Point Load Index (Is_{50})

(b) Schmidt hammer rebound number (R_n)
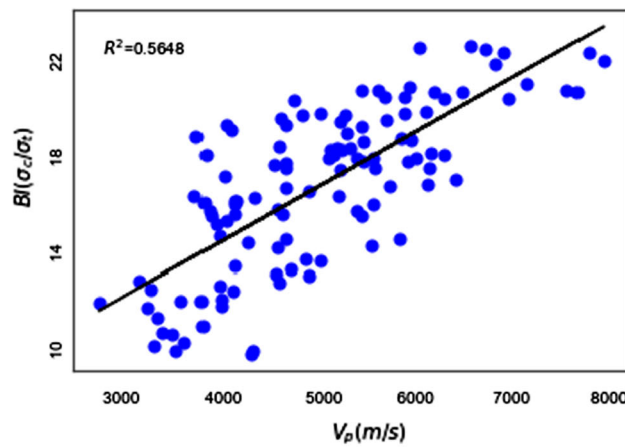
(c) Wave velocity (V_p)

Fig. 6 Performance of the BI prediction using simple regression analysis
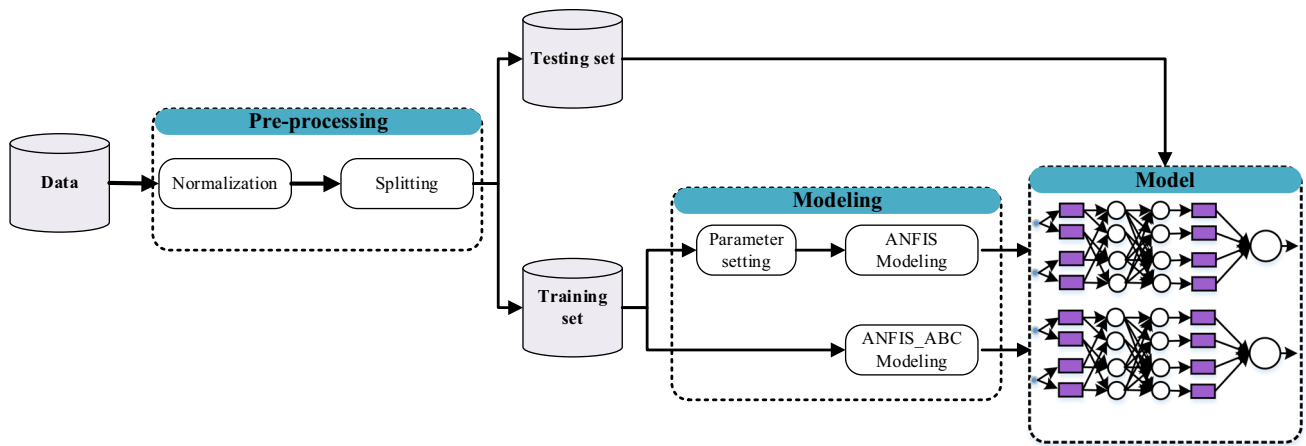
Fig. 7 Experiments framework

(a) GbellMF for variable Is_{50}

(b) GbellMF for variable R_n

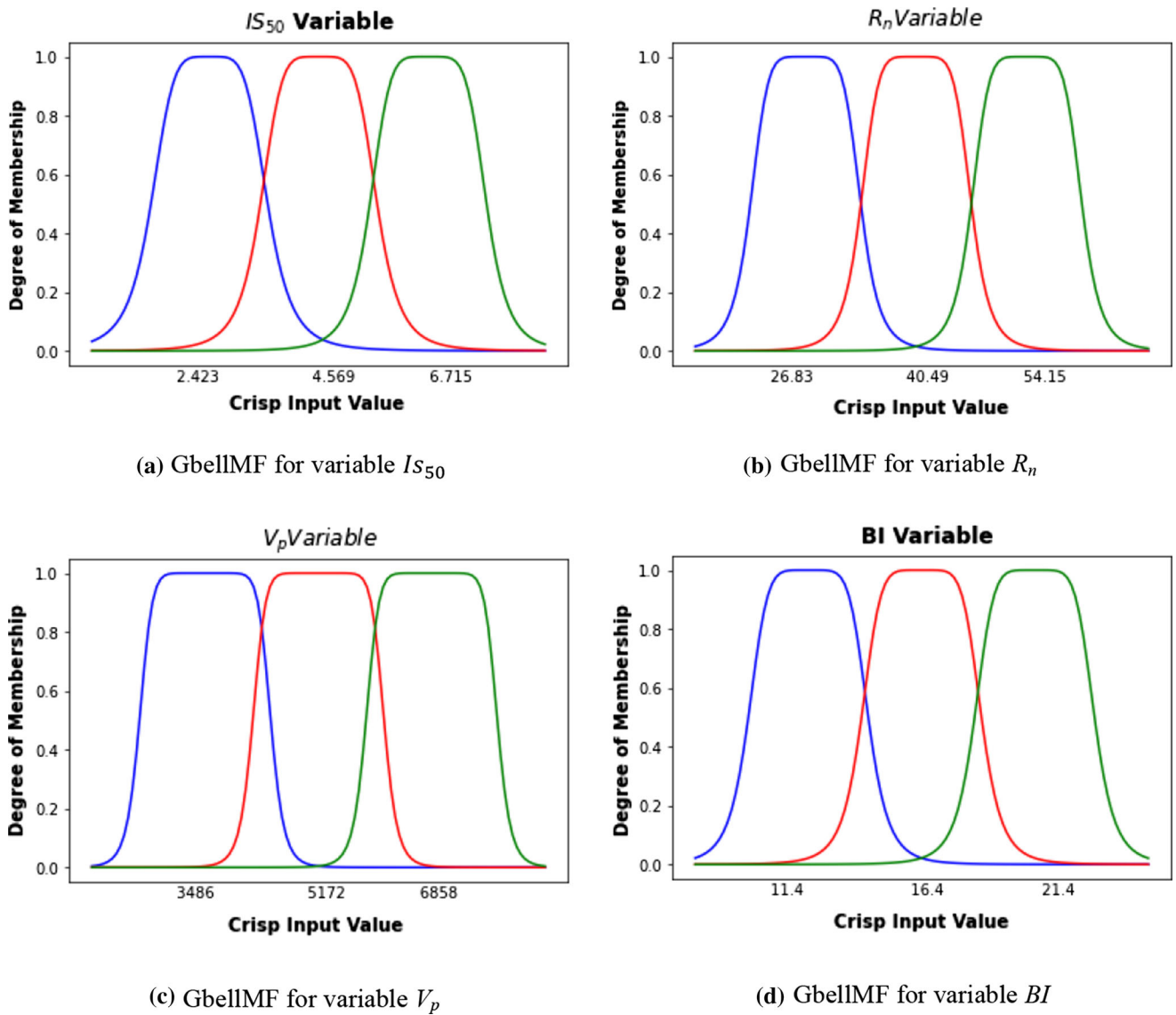(c) GbellMF for variable V_p

(d) GbellMF for variable BI

Fig. 8 MFs for variables used in modelling

used in this study is strength and the level of compactness, it is expected to increase BI values by increasing R_n, V_p, and Is_{50} rock index tests. However, the question is which equation type can perform better in describing the best relationships between these inputs and BI values. According to the results presented in Table 1, linear and exponential relationships demonstrate a stronger correlation between BI and (R_n and V_p). Correspondingly, exponential equation could achieve the best R^2 value for Is_{50}. Figure 6a, b, and c shows the obtained relationships between BI and Is_{50}, R_n, and V_p, respectively. The results are statistically significant for the relationships, and they are in agreement with previous investigations [5]. The results also suggest that if all three input parameters were used in the same relationship, the prediction of the BI of rock would be more accurate. Hence, in the following section, steps of the used AI models in predicting the rock BI will be described in detail.

4 AI model development and assessment

This section explains how to carry out the experiments using ANFIS and ANFIS_ABC predictive models. Figure 7 shows the experiment process. In the first step, the data are normalized using the Min–Max normalization technique. All experiments were conducted on 80% of the dataset (i.e., 90 samples), which were randomly selected, as the training set. Twenty percent of the dataset (i.e., 23 instances) was selected for the testing stage. It is worth mentioning that the combination of (80–20) for training and testing datasets was used in accordance with suggestions available in the literature [71–73]. Both ANFIS and
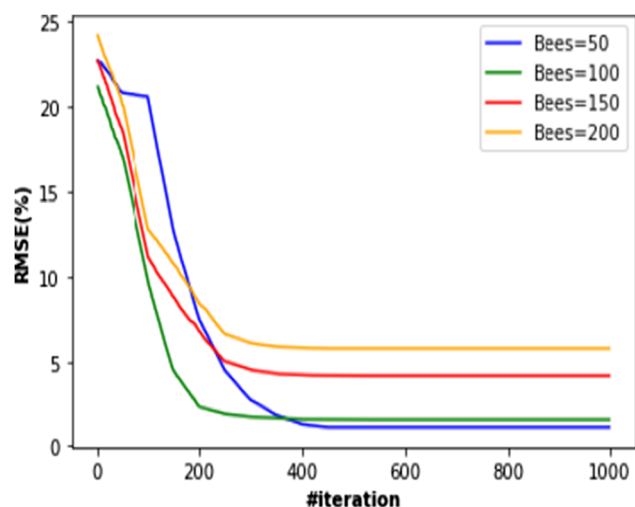
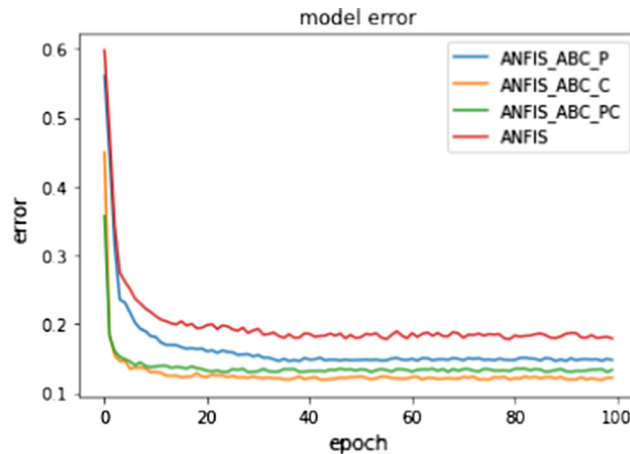**Fig. 9** ANFIS_ABC model performance in terms of various numbers of bee

Fig. 10 Average error of the developed models in terms of the number of epoch

ANFIS_ABC models were built using the training set. Once models are generated, the testing set was used to evaluate the performance of the developed models using different PIs.

4.1 ANFIS

In order to predict the BI of rock samples using ANFIS, three fuzzy input variables (i.e., R_n, V_p, IS_{50}) were used. The Generalized Bell (Gbell) function fuzzy membership was chosen for these variables. It is important to express that some other MFs such as trapezoidal and triangular were investigated, and the best results were obtained using the GBell MF type. The Gbell MF is defined in the following form:

$$Bell(x, a, b, c) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}} \quad (16)$$

where x is a 1D array of values and a, b, and c are used to control width, center, and slop, respectively. The first input variable is Is_{50}, which its MF obtained by the proposed ANFIS model is depicted in Fig. 8a. The linguistic variables for this fuzzy set are low, medium, and high. The second fuzzy input variable is the R_n where MF obtained by the proposed ANFIS model is shown in Fig. 8b. The MFs of the third input parameter (V_p) is shown in Fig. 8c. The only fuzzy output variable is the BI value. The fuzzy set for competition radius is demonstrated in Fig. 8d. The developed ANFIS model with the described structure was constructed to predict the rock BI values, and its results will be discussed in detail later.

Table 2 Performance prediction of the ANFIS-based models to predict the rock BI

| PI Algorithm	RSME		SI		MAE		R^2		Total ranking
	Train	Test	Train	Test	Train	Test	Train	Test	
ANFIS	0.9164	0.8849	0.0742	0.0547	0.985	0.9157	0.853	0.8613	8
Ranking	1	1	1	1	1	1	1	1	
ANFIS_ABC_P	0.7488	0.7744	0.0607	0.0486	0.8098	0.8071	0.9563	0.9421	21
Ranking	3	2	3	2	3	2	3	3	
ANFIS_ABC_C	0.7747	0.7618	0.0617	0.046	0.8272	0.7873	0.9478	0.9356	19
Ranking	2	3	2	3	2	3	2	2	
ANFIS_ABC_PC	0.5872	0.6067	0.0537	0.041	0.7132	0.6853	0.9652	0.96	32
Ranking	4	4	4	4	4	4	4	4	
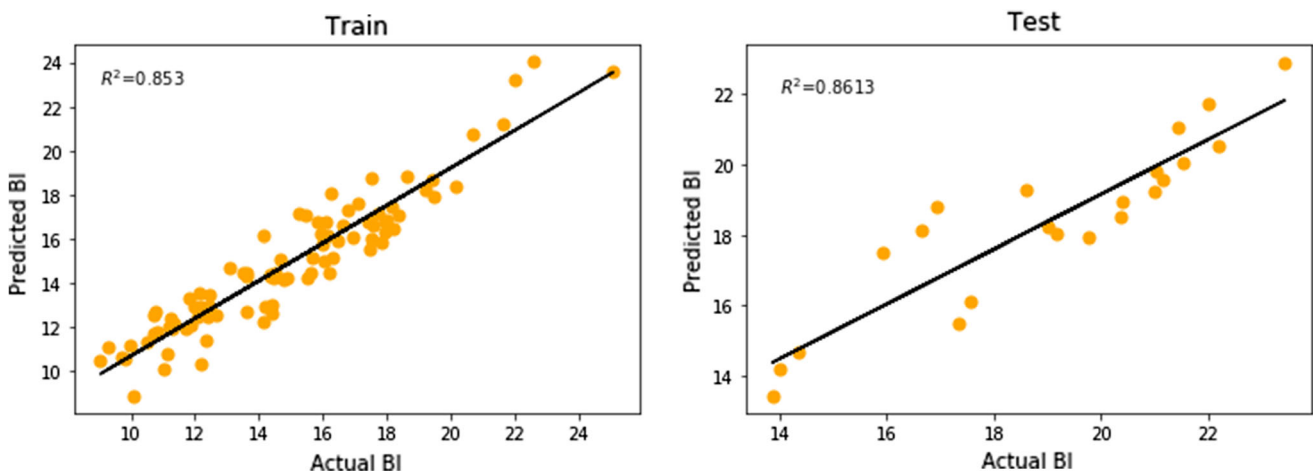
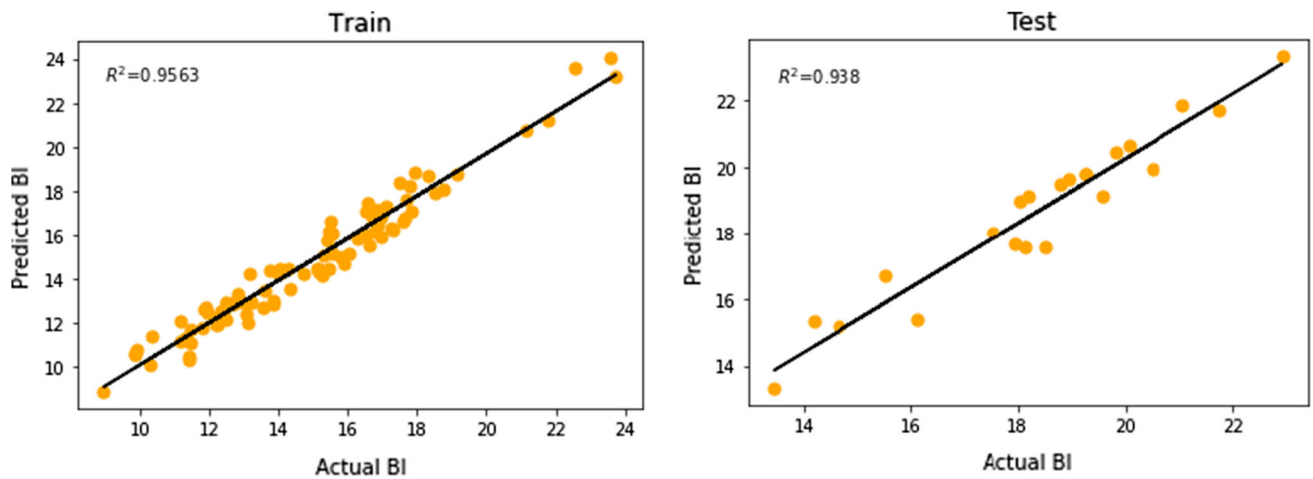**Fig. 11** ANFIS model performance prediction to estimate the rock BI

Fig. 12 ANFIS_ABC_P model performance prediction to estimate the rock BI
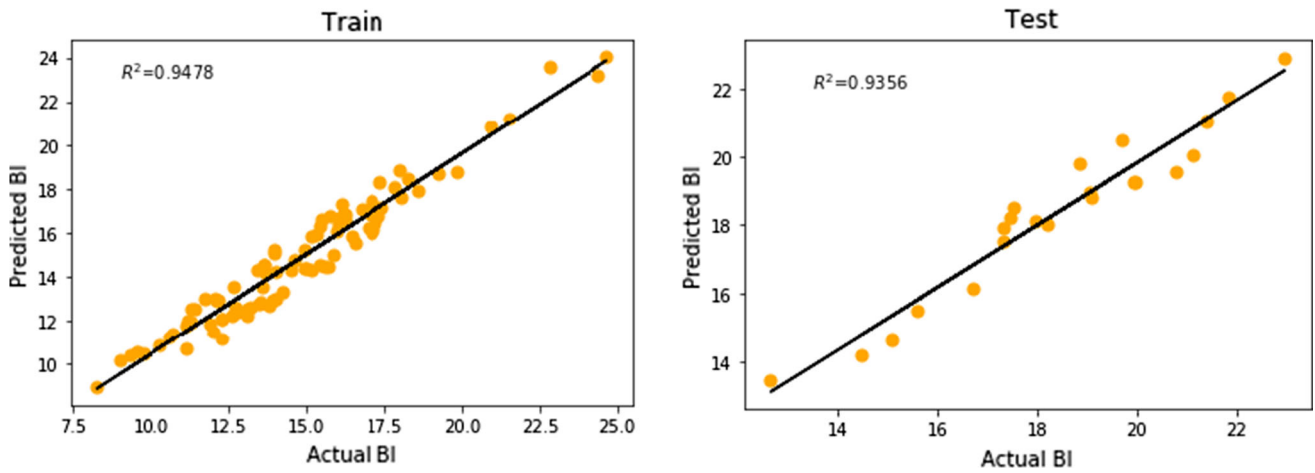
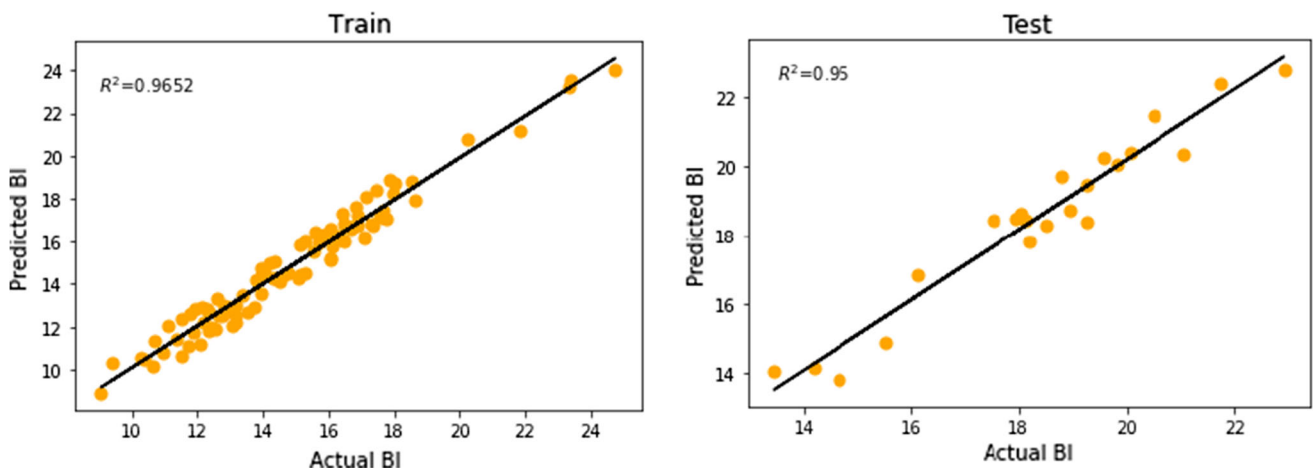**Fig. 13** ANFIS_ABC_C model performance prediction to estimate the rock BI

Fig. 14 ANFIS_ABC_PC model performance prediction to estimate the rock BI

Fig. 15 Assessing performance of ANFIS_ABC models in predicting BI using testing data on models trained with different number of bees
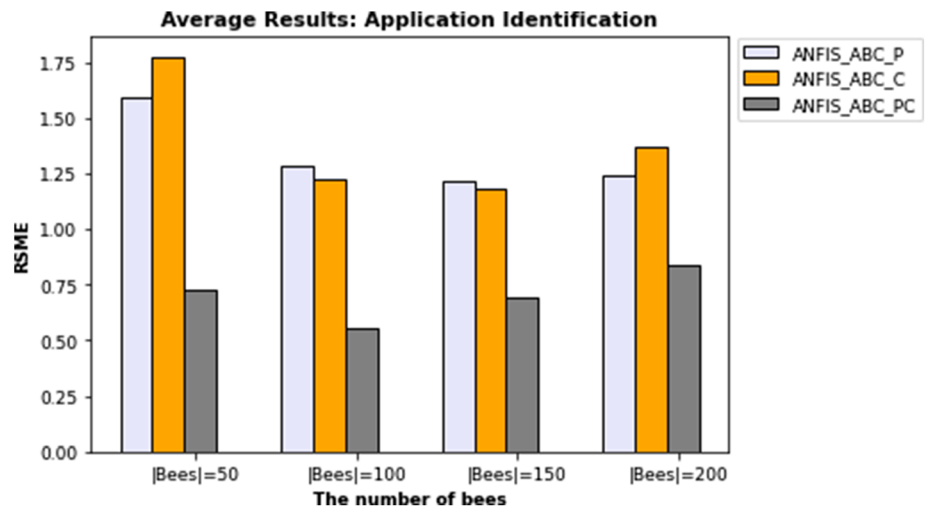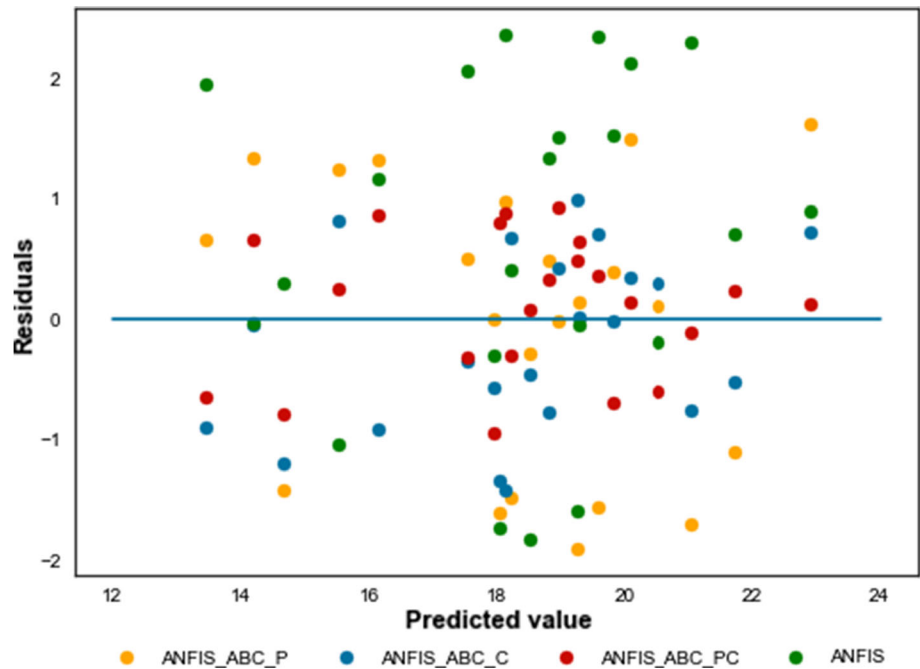
Fig. 16 Assessing performance of ANFIS_ABC models in predicting BI using testing data

4.2 ANFIS_ABC

Before starting the ANFIS_ABC modeling to estimate the target variables, the ANFIS and ABC parameters must be initialized. In this paper, three improved ANFIS algorithms were proposed according to the layer in which the ABC algorithm is employed, including precise layer (ANFIS_ABC_P), consequence layer (ANFIS_ABC_C), and both precise and consequence layers (ANFIS_ABC_PC). In ANFIS_ABC_P, three parameters in the *Fuzzification layer* (i.e., a, b, c) are encoded in terms of a population of individuals and ABC algorithm is used as the search mechanism for optimizing parameters values. On the other hand, the parameters of the *Defuzzification layer* (i.e., p, q, r) is represented as solutions in ANFIS_ABC_C. The ABC algorithm is employed to find the best values for these parameters. ANFIS_ABC_PC is the combination of two algorithms of ANFIS_ABC_P and ANFIS_ABC_C, where all parameters in both *Fuzzification and Defuzzification* layers are encoded to be optimized using ABC algorithm.

The number of employed bee (i.e., food sources) and maximum iteration are defined as 50 and 1000, respectively. It has been proven that ABC algorithm can achieve a high degree of performance when the *limit* value is $SN*D$, where D represents the length of solutions and SN represents the number of the employed bees or population size [65]. In the following section, the constructed ANFIS_ABC models will be evaluated and discussed.

5 Results and discussion

This section provides the results obtained from the experiments carried out using ANFIS_ABC in comparison with the basic or pre-developed ANFIS. To assess the performance of the ANFIS_ABC algorithm in terms of RMSE, a parametric study was conducted. In this parametric study, the number of iterations increases for four different population sizes (i.e., the number of bees). Different predictors were modeled with various number of bees (i.e., 50, 100, 150, and 200) and iterations, which the results of predictive models construction are depicted in Fig. 9. It can be seen that RMSE values of the developed models increase when the number of employed bees increases. However, no significant change in RMSE beyond the maximum cycle number can be observed. This may be associated with the fact that the bees are gathered in places where the best answer exists.

Figure 10 shows the average error on the testing datasets in terms of the number of epoch. This experiment was carried out using 20 epochs in the modeling process. As it can be seen, ANFIS_ABC could yield lower error compared to ANFIS algorithm in predicting BI of the rock samples. The average error for ANFIS_ABC was about 3% lower than the ANFIS technique. According to Fig. 10, all hybrid ANFIS models, i.e., ANFIS_ABC_P, ANFIS_ABC_C, and ANFIS_ABC_PC received better performance prediction compared to a pre-developed ANFIS model to predict the rock BI. It is because of using ABC as

(a) Contour plot for variable Is_{50}

(b) Contour plot for variable R_n

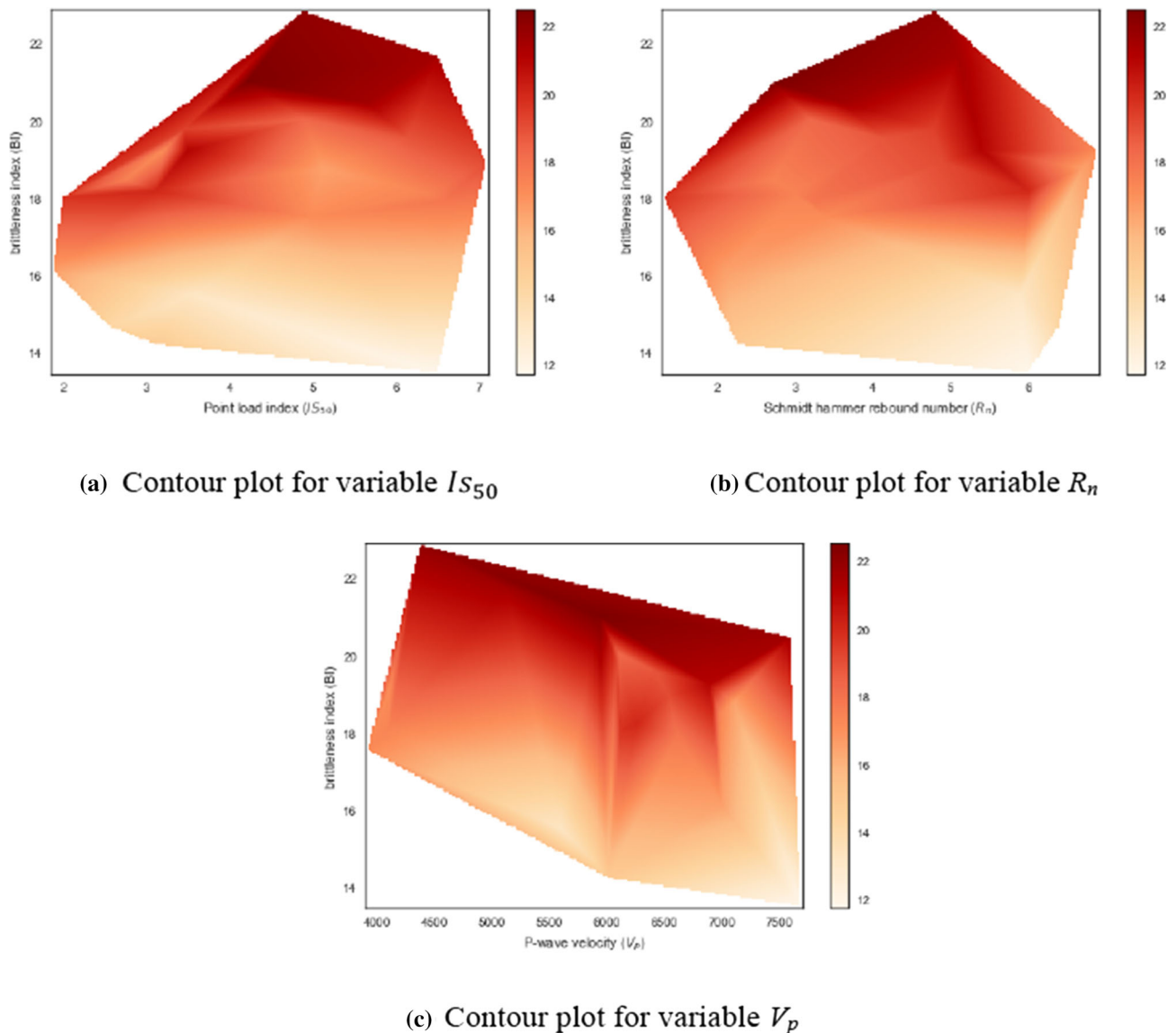(c) Contour plot for variable V_p

Fig. 17 The 2D contour plots for ANFIS_ABC_P model

a powerful optimization algorithm to optimize MFs of ANFIS.

Table 2 shows the performance of the predictive models in terms of the different PIs, including RMSE, SI, MAE, and R^2. According to this table, the ANFIS_ABC_PC algorithm yielded a better agreement between actual and estimated BI values and the lowest error compared with three other developed models. To select the best predictor with the highest performance, a ranking technique proposed by Zorlu et al. [74], was utilized to assign a rank to each model for training and testing data samples. In this ranking method, each PI receives a value according to its performance capability. For example, considering the R^2 values of the training datasets for all developed models,

values of 1, 2, 3, and 4 were assigned to ANFIS (with R^2 of 0.853), ANFIS_ABC_C (with R^2 of 0.9478), ANFIS_ABC_P (with R^2 of 0.9563), and ANFIS_ABC_PC (with R^2 of 0.9652), respectively. As shown in Table 2, ANFIS_ABC_PC model receives the greatest ranking value (i.e., 32). While, ranking values of 8, 21 and 19 were obtained for ANFIS, ANFIS_ABC_P, and ANFIS_ABC_C, respectively in predicting BI values of the rock samples. Thus, ANFIS_ABC_PC model could provide more accurate prediction results of BI compared to other built models.

Figures 11, 12, 13, 14 show the actual BI values in comparison with BI values predicted by the ANFIS-based models for both train and test stages. According to these
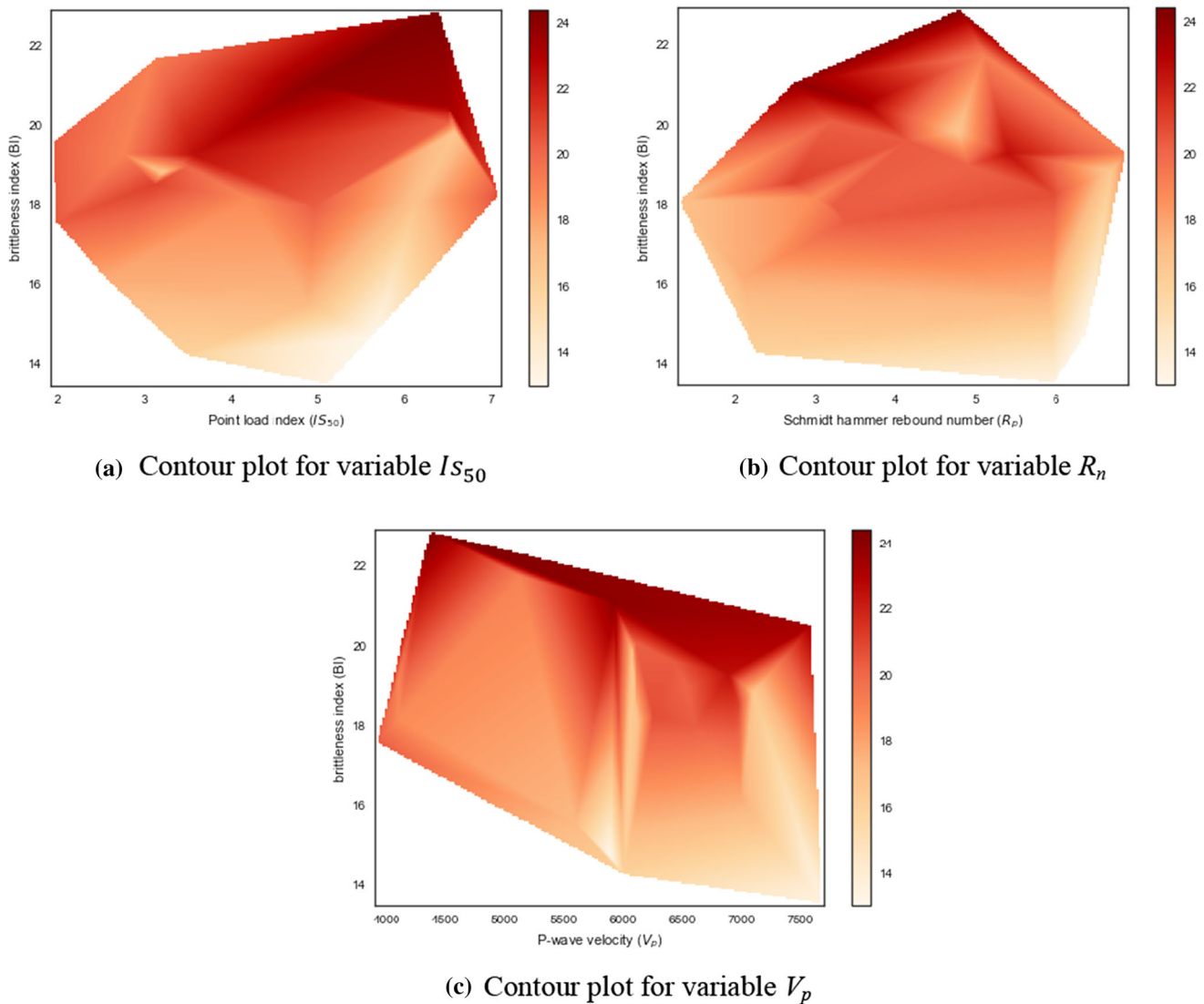
(a) Contour plot for variable Is_{50}

(b) Contour plot for variable R_n

(c) Contour plot for variable V_p

Fig. 18 The 2D contour plots for ANFIS_ABC_C model

figures, it can be seen that the ANFIS_ABC_PC with the R^2 of 0.9652 for training data and 0.950 for testing data is the most reliable model in predicting the BI of rock. The ANFIS results were 0.853 and 0.861 based on R^2, according to its train and test stage, respectively. It is worth mentioning that all hybrid-based ANFIS models received a more accurate results in comparison with a pre-developed ANFIS model. Form these figures, it is demonstrated that ANFIS_ABC models, especially ANFIS_ABC_PC, provide a relatively closer prediction BI values compared to a pre-developed ANFIS model.

Figure 15 shows RMSE values of ABC-based ANFIS models when the number of bees varies. It has been demonstrated that the best values are obtain when bees size are 100 and 150.

Figure 16 compares performance prediction of the four used predictive models (i.e., ANFIS, ANFIS_ABC_P, ANFIS_ABC_C, and ANFIS_ABC_PC) for the testing samples (23 data samples). This figure shows that the BI values predicted by ANFIS-ABC_PC are much closer to the measured BI values compared to other three proposed models. Therefore, this model possesses superior predictive ability than the other predictive models. In addition, Figs. 17, 18, 19 present the 2D contour plot obtained from the intelligent models (i.e., ANFIS_ABC_P (a), ANFIS_ABC_C (b), and ANFIS_ABC_PC (c)). These figures display the relationships between the two input variables, actual BI, and the predicted BI value. Darker regions indicate the better prediction BI values, while the lighter areas demonstrate the worse predicted BI values.
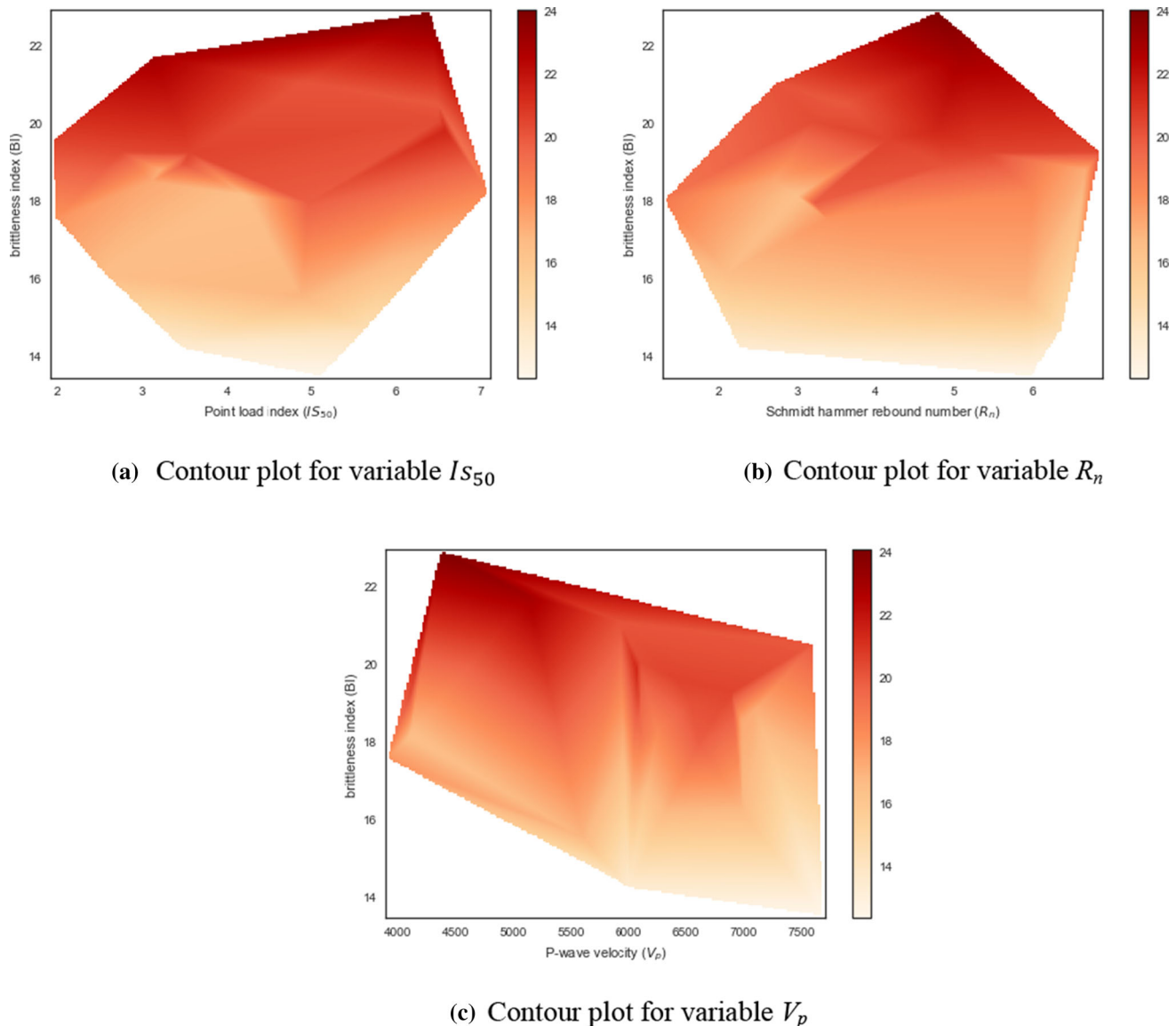
(a) Contour plot for variable Is_{50}

(b) Contour plot for variable R_n

(c) Contour plot for variable V_p

Fig. 19 The 2D contour plots for ANFIS_ABC_PC model

Based on the figures, we can see that our proposed models could have a better prediction for Is_{50} values. On the other hand, our models achieved the worse prediction values for the Rn values.

In comparison with the similar published studies in the field of BI prediction, the present study provides a higher performance prediction for estimating BI of the rock. Armaghani et al. [5] examined hybrid support vector machine (SVM) with feature selection (FS), i.e., SVM-FS technique to predict BI of the rock and introduced the mentioned model with R^2 of 0.85. In another research, Sun et al. [26] used and proposed a random forest technique with R^2 equal to 0.9 in estimating BI of the rock. A hybrid model (i.e., FA-ANN) was developed in the study conducted by Koopialipoor et al. [1] to forecast BI of the rock.

They obtained a R^2 of 0.92 for their developed model. In another relevant study, Yagiz and Gokceoglu [13] introduced a FIS model with a suitable performance to predict BI of the rock and achieved a R^2 of 0.72 for their model. These studies and their performances showed that the developed models in this study could be introduced as a new, powerful, and applicable approach for solving the rock BI problem.

6 Conclusion

In this research, the accuracy of an ANFIS model was significantly improved using an ABC algorithm. To this end, a series of laboratory tests were performed and a

database comprising 113 datasets of varying rock types was compiled. Three different versions of ANFIS_ABC algorithms were developed and ranked against a benchmark (i.e., pre-developed) ANFIS algorithm using a variety of model performance criteria. The results show that the ANFIS_ABC algorithm reduced the average prediction errors by about 2%. The developed ANFIS_ABC models registered an R^2 and RMSE of 63% and 91%, respectively. The developed ANFIS_ABC_PC model had a higher prediction accuracy compared to other ANFIS-based models, in terms of both the accuracy R^2 and system errors. The models developed in this research can assist in the prediction of the BI of rock for a range of rock construction projects. The success of ANFIS_ABC models in predicting the BI of rock may indicate that ANFIS_ABC models may also be successfully used for the prediction of the tensile strength of rock. As a next research opportunity, improving the performance of optimization parameters using k-fold cross-validation can be considered, where an ensemble learning on different ANFIS models can be built. In addition, other optimization techniques such as the grasshopper or the Harris hawks optimization algorithm can be combined with ANFIS to increase the prediction accuracy of the models.

Declarations

Conflict of interest The authors declare no conflict of interest.

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