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Full Length Article

An evolutionary adaptive neuro-fuzzy inference system for estimating field penetration index of tunnel boring machine in rock mass

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ABSTRACT

Field penetration index (FPI) is one of the representative key parameters to examine the tunnel boring machine (TBM) performance. Lack of accurate FPI prediction can be responsible for numerous disastrous incidents associated with rock mechanics and engineering. This study aims to predict TBM performance (i.e. FPI) by an efficient and improved adaptive neuro-fuzzy inference system (ANFIS) model. This was done using an evolutionary algorithm, i.e. artificial bee colony (ABC) algorithm mixed with the ANFIS model. The role of ABC algorithm in this system is to find the optimum membership functions (MFs) of ANFIS model to achieve a higher degree of accuracy. The procedure and modeling were conducted on a tunnelling database comprising of more than 150 data samples where brittleness index (BI), fracture spacing, α angle between the plane of weakness and the TBM driven direction, and field single cutter load were assigned as model inputs to approximate FPI values. According to the results obtained by performance indices, the proposed ANFIS_ABC model was able to receive the highest accuracy level in predicting FPI values compared with ANFIS model. In terms of coefficient of determination (R^2), the values of 0.951 and 0.901 were obtained for training and testing stages of the proposed ANFIS_ABC model, respectively, which confirm its power and capability in solving TBM performance problem. The proposed model can be used in the other areas of rock mechanics and underground space technologies with similar conditions.

1. Introduction

Predicting performance of tunnel boring machine (TBM) is an essential task when estimating construction period and cost of pre-construction stage. Therefore, in the schedule preparation of a tunnelling project constructed by TBM, it is necessary to estimate the performance of TBM (Yagiz et al., 2009). This performance can be evaluated by various indicators, such as penetration rate (PR) (Yagiz and Karahan, 2011; Armaghani et al., 2017; Ma et al., 2020), advance rate (AR) (Armaghani et al., 2019; Zhou et al., 2020a), and field penetration index (FPI) (Delisio et al., 2013; Yagiz, 2017). Although PR and AR can be considered as suitable indicators for evaluation of TBM performance, they cannot provide useful assessment when tunnel diameters and machine specifications are diverse due to the lack of consideration of the thrust force exerted by the TBM (Yagiz, 2017). FPI is the ratio of cutting force to penetration for each complete round of the TBM head (Adoko and Yagiz, 2019). Unlike other parameters, FPI can be employed for evaluation of rock mass characteristics with no impact on TBM operating parameters. However, it is difficult to predict FPI because of the uncertainty and heterogeneity of the ground. Misestimating TBM performance can delay the project, thus leading to additional costs.

Different studies introduced empirical and computational techniques to determine TBM performance. These studies are categorized into three classes: (1) theoretical/empirical

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Table 1
A summary of studies on TBM performance prediction based on ML models.

Database description	Data size	Output	Model	R^2	Reference
Yingsong water diversion project (China)	728	FPI	Deep belief network	0.78	Feng et al. (2021)
Queens water tunnel (USA)	151	FPI	FIS	0.79–0.92	Adoko and Yagiz (2019)
Shenzhen metro line (China)	503	PR	Gray wolf optimizer-feature weighted-multiple kernel-SVM	0.894–0.946	Yang et al. (2020)
PSRWT tunnel (Malaysia)	1286	PR	Gene expression programming	0.829–0.855	Armaghani et al. (2018a)
10 km data from Zagros tunnel (Iran)	–	PR	ANN	0.69	Eftekhari et al. (2010)
PSRWT tunnel (Malaysia)	1286	AR	SVM-moth flame optimization	0.962–0.972	Zhou et al. (2021)
Queens water tunnel (USA)	151	PR	Support vector regression, decision tree	–	Zhang et al. (2020b)
PSRWT tunnel (Malaysia)	1286	AR	Particle swarm optimization-ANN	0.96	Armaghani et al. (2019)
Karaj–Tehran tunnel (Iran), Gilgel Gibe II hydroelectric project (Ethiopia), Queens water tunnel (USA)	185	PR	ANN	0.94	Javad and Narges (2010)
Queens water tunnel (USA)	151	PR	ANN	0.77–0.94	Yagiz et al. (2009)
PSRWT tunnel (Malaysia)	1286	PR	Group method of data handling	0.924–0.946	Koopialipoor et al. (2018)
Karaj–Tehran tunnel (Iran)	46	PR	ANN	0.83	Salimi and Esmaeili (2013)
PSRWT tunnel (Malaysia)	1286	PR	Imperialism competitive algorithm-ANN	0.91	Armaghani et al. (2017)
Queens water tunnel (USA)	151	PR	Support vector regression	0.7715	Mahdevari et al. (2014)
Queens water tunnel (USA)	151	PR	FIS	0.893	Ghasemi et al. (2018)
Queens water tunnel (USA) and Gilgel Gibe II hydroelectric project (Ethiopia)	177	PR	Neuro-fuzzy	0.69	Oraee et al. (2012)
Queens water tunnel (USA)	151	PR	Bayesian inference	0.75–0.93	Adoko et al. (2017)
PSRWT tunnel (Malaysia)	1286	AR	Genetic programming	0.91	Zhou et al. (2020a)
Queens water tunnel (USA)	151	FPI	Adoptive neuro-FIS with artificial bee colony (ABC) algorithm (ANFIS_ABC)	0.901–0.951	This study

approaches, (2) statistical approaches, and (3) soft computing approaches. The aim of the theoretical/empirical category is to formulate cutter force equilibrium via the cutting mechanism and the acting forces to evaluate PR (Entacher et al., 2014; Yang et al., 2016a, b, 2018). To verify the theoretical model, a full-scale cutting experiment should be performed by laboratory investigation. Due to its high cost, full-scale cutting machines cannot be fully accessed by a theoretical model. Therefore, several theoretical/empirical approaches were developed to find the relationships between the TBM performance and the affecting factors based on laboratory data. However, these empirical models are not always good for different case studies and many researchers reported their shortcomings in predicting the TBM performance (Grima and Bruines, 2000; Benardos and Kaliampakos, 2004). On the other hand, statistical approaches (Hassanpour et al., 2016; Salimi et al., 2018) were also applied to solving such problems, however, their prediction capacities are not accurate enough. In recent years, the applicability of machine learning (ML) and artificial intelligence (AI) techniques in solving engineering problems has been reported to be feasible by many researchers (Zhou et al., 2016, 2019; Ghasemi et al., 2018; Yagiz et al., 2018; Koopialipoor et al., 2019; Armaghani and Asteris, 2020; Harandizadeh and Armaghani, 2020; Huang et al., 2020, 2021; Zhang et al., 2020a, 2021a, b; Telikani et al., 2021).

Different ML and AI models were developed to estimate the TBM performance. Some of these techniques are artificial neural networks (ANNs) and hybrid ANN groups (Benardos and Kaliampakos, 2004; Yagiz et al., 2009; Armaghani et al., 2017; Koopialipoor et al., 2018), support vector machine (SVM) and

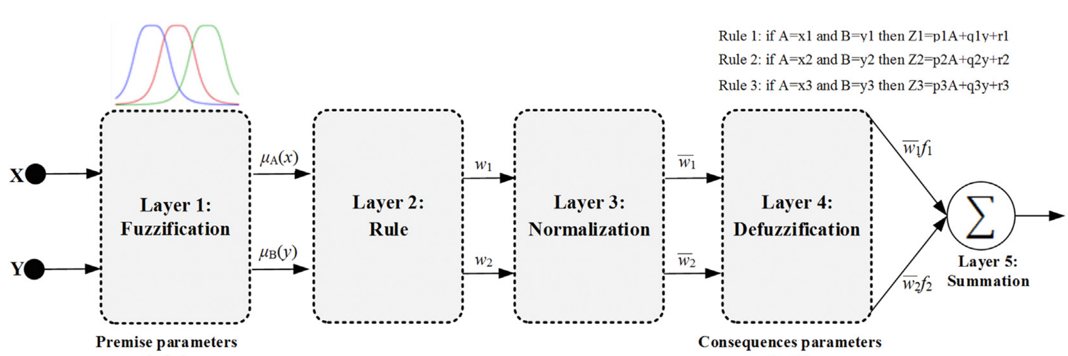


Fig. 1. Schematic diagram of the five-layer architecture of ANFIS.

hybrid-SVM groups (Zhou et al., 2021; Mahdevari et al., 2014), fuzzy-based techniques (Simoes and Kim, 2006; Ghasemi et al., 2014), genetics-based approaches (Armaghani et al., 2018a; Samaei et al., 2020; Zhou et al., 2020a), and Bayesian prediction (Adoko et al., 2017). Zhang et al. (2020b) proposed three approaches of TBM performance prediction using Bayesian optimization, where Bayesian optimization was employed to determine the optimized hyper-parameters of the ML techniques. In another study carried out by Zhou et al. (2021), the hyper-parameters of the SVM technique were optimized through the use of various optimization algorithms (OAs). A practical and powerful gene-based intelligent formula was proposed in Armaghani et al. (2018a) to forecast the PR of TBM. A multiple kernel-SVM-based technique was introduced by Yang et al. (2020) as another ML solution. An interesting ML-hybrid technique based on extreme gradient boosting was introduced and successfully applied by Zhou et al. (2020b) for predicting the PR of TBM. Specifically in the case of FPI prediction, in fact, there are only a few studies aiming at prediction of FPI using ML models. Feng et al. (2021) introduced an ML approach focusing on deep learning in order to predict FPI values. In another study, a fuzzy inference system (FIS) was applied and proposed by Adoko and Yagiz (2019) for estimate of FPI values and a coefficient of determination (R^2) ranging between 0.79 and 0.92 was obtained by these researchers in predicting FPI. Table 1 shows some of the previous studies on TBM performance prediction based on AI models.

Since there are different uncertainties in TBM performance (e.g. machine specifications, rock mass/material properties), the FPI can be considered as fuzzy set theory. Because of its convenience in managing uncertainty, fuzzy set theory has been applied to developing approaches for estimating different aspects of TBM performance, i.e. energy required for TBM (Acaroglu et al., 2008), drift and torque needs of TBM (Acaroglu, 2011), performance estimate of road header (Yazdani-Chamzini et al., 2013), and hard rock TBM (Armaghani et al., 2018a; Mikaeil et al., 2018).

This research integrates two concepts of optimization computing and fuzzy set theory. In this regard, a hybrid intelligent system is proposed in which ABC algorithm is utilized as a parameter optimizer for the ANFIS. The reason for this is that setting parameters of ANFIS needs a profound knowledge of ML and fuzzy set theory. The parameters used in ANFIS are optimized by the ABC algorithm during the training phase (Karaboga and Kaya, 2016). Derivative and metaheuristic methods are two types of algorithms that are used in training ANFIS. In spite of the ability of ANFIS in solving engineering problems, it has some shortcomings, such as slow rate of learning and entrapment in local minima (Hasanipanah et al., 2017; Shahnazar et al., 2017). To address these challenges, ABC algorithm is employed to optimize the parameters of ANFIS model and an improved version of ANFIS is proposed to predict FPI values. Two types of parameters, which are associated with fuzzy sets in ANFIS model, are tuned by the ABC algorithm. The parameters are encoded as solutions and ABC algorithm is applied as search mechanism to find the best solution as the final parameters of the ANFIS model.

The structure of this study is planned as follows: Section 2 explains fundamental concepts of ANFIS, and ABC algorithms used in this research. Section 3 describes the dataset collected for this paper. Section 4 presents a hybrid evolutionary ANFIS model which employs the ABC approach in the parameter adjusting step of ANFIS to improve the efficiency of TBM performance prediction. Section 5 evaluates the proposed algorithm compared with others based on different criteria. Finally, Section 6 provides a summary of the paper.

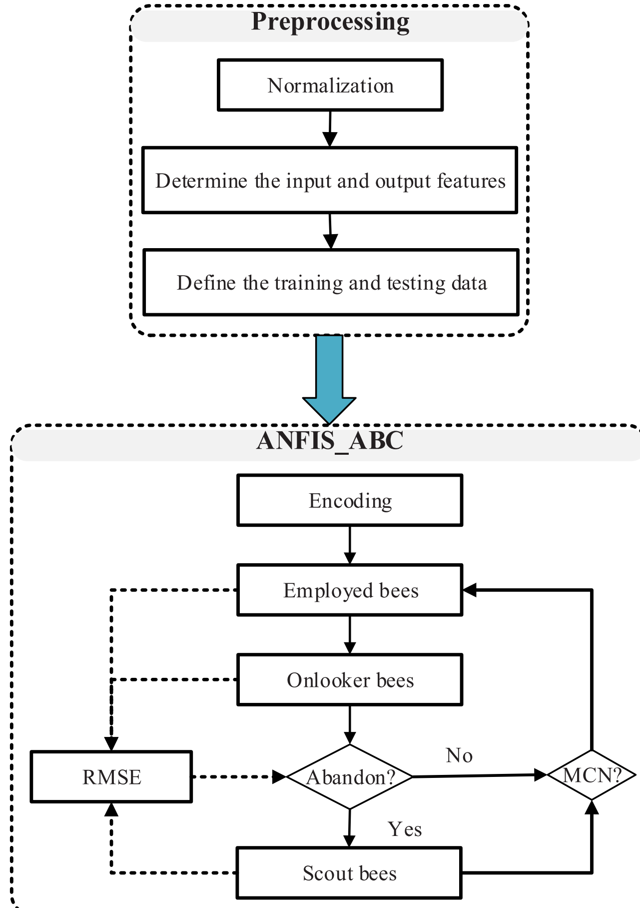


Fig. 2. The framework of ANFIS_ABC method to predict FPI values. RMSE is the root mean square error, and MCN is the Maximum Cycle Number.

2. Material and methods

2.1. ANFIS background

ANFIS consists of five layers, i.e. fuzzification, rule, normalization, defuzzification, and summation (Fig. 1). ANFIS model is trained by optimizing the parameters belong to the 1st and the 4th layers, which are called premise (antecedent) parameters and consequence (conclusion) parameters, respectively.

(1) Layer 1: Fuzzification

This layer obtains fuzzy cluster input values using membership functions (MFs). MFs are formed in fuzzification layer using parameters in antecedent part, (i.e. a, b, c). In fact, degree of each MF is determined by

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

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

where μ_{A_i} is the membership degree of the function i, gbellmf is a function that computes fuzzy membership values using a generalized bell-shaped membership function, x is the input variable, O_i^1

is the output value of the node i in the layer 1, and $\mu_{A_i}(x)$ is the membership degree of the function i for x.

(2) Layer 2: Rule

The rule layer creates weights (w_i) for the rules using MFs calculated in the first layer. The weights are generated by multiplying the MFs:

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

(3) Layer 3: Normalization

This calculates normalized weight of each rule, where the normalized weight is the percentage of the firing strength of a rule to the total of all firing strengths:

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

where $\overline{w_i}$ is the output of the normalization layer.

(4) Layer 4: Defuzzification

Defuzzification layer computes weights of the rules in each node by

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}[(p_i x)(q_i x + r_i)] \tag{5}$$

where p_i, q_i and r_i are three conclusion parameters. As a rule, the number of the conclusion parameters for each rule should be more than that of input.

(5) Layer 5: Summation

The predicted value in the last layer is obtained by accumulating all outputs obtained for each rule in the fourth layer by

$$O_i^5 = \sum_i \overline{w_i}f_i = \frac{\sum_i \overline{w_i}f_i}{\sum_i W_i} \tag{6}$$

where O_i^5 is the overall output.

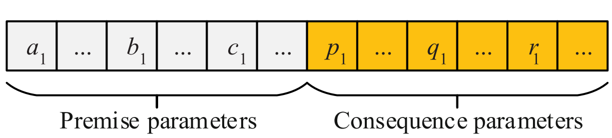


Fig. 3. Individual representation.

2.2. ABC algorithm

ABC, introduced by Karaboga (2005), has been inspired by the foraging characteristic of honey bee (Telikani et al., 2020a). A bee colony consists of three groups (see Appendix): employed, onlooker, and scout bees. Employed bees occupy a half portion of colonies and onlooker bees occupy the other half. In ABC algorithm, there is one employed bee for each food source (Akay and Karaboga, 2012). When an employed bee abandons its food source, it is considered as a scout bee.

The first step of ABC is to randomly generate initial food sources using Eq. (7). Structure of a food source or solution is a vector with the size of D and represents a given problem.

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

where SN and D are the population size defined by the user and the size of solutions, respectively; rand(0, 1) is a function that produces a random value between 0 and 1; $X_{\min,j}$ and $X_{\max,j}$ are the lowest and highest values of the cell j, respectively; i is the index of the solution that is selected randomly; and j is a random number between 1 and D.

An employed bee modifies a solution based on Eq. (8). When a new solution is generated, its nectar amount is computed. The employed bee memorizes the position of the new solution and moves to a new food source to see if the quality of the new one is better than the old one.

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

where $\theta_{i,j}$ is a random value in range of $[-1, 1]$; V_i, X_i and X_k are the new, current, and the neighbour individuals, respectively; and k is the index of the solution that is selected randomly.

In the onlooker bee phase, a probabilistic selection process is performed to calculate the chance for solution i (see Eq. (9)). The probability value P_i is calculated based on the nectar amount of the food sources evaluated by the employed bees (Lin et al., 2016).

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

where f_i is the quality of the individual i. Once P_i is computed, it is compared with a random value between 0 and 1. If the P_i is larger than the value, the onlooker bees go to the area X_i located at food source to determine a new neighbouring food source. Once the onlooker bees reach to the neighbourhood, each bee generates a new solution using Eq. (8). In this phase, if the quality of a solution cannot be improved after a given number of cycles (i.e. "limit"), the employed bee leaves the neighbour and is converted to a scout bee and performs a random search to explore new food sources.

Table 2
Descriptive statistics of input and output parameters.

Variable	Unit	Minimum	Maximum	Average	Standard deviation	Variance
BI	kN/mm	25	58	35	8.45	71.5
Fracture spacing	M	0.8	2	1	0.644	0.415
α angle	°	2	89	45	23.27	541.9
Field single cutter load	kN	236	383	321	34.3	1176.5
FPI	kN/(mm rev)	45.21	147.66	81	18.59	345.66

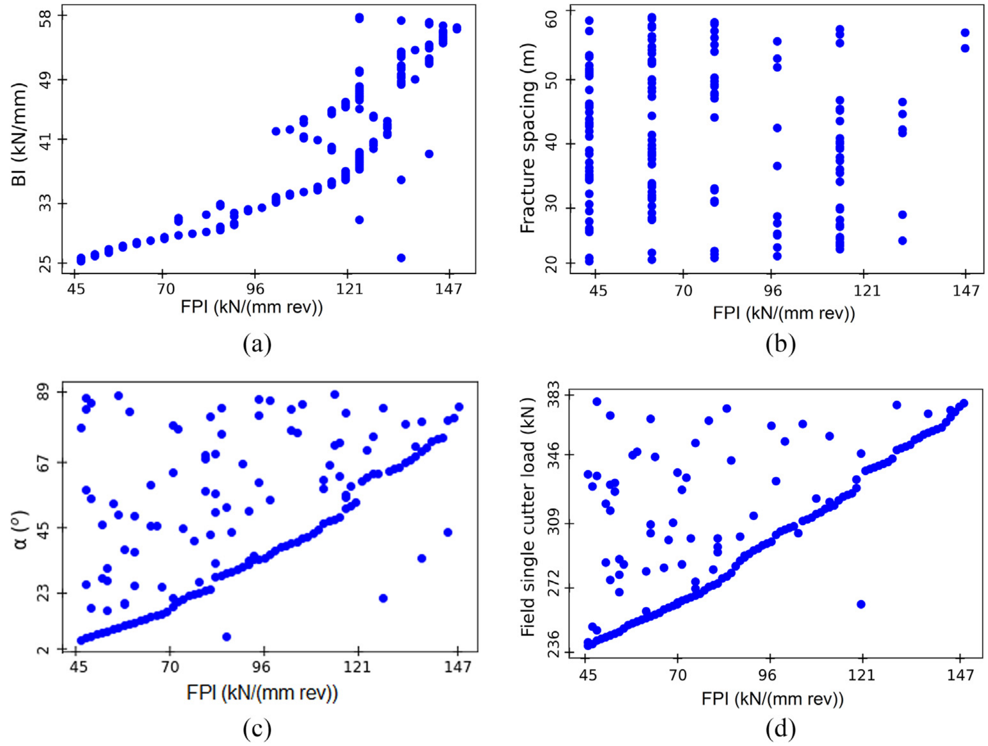


Fig. 4. Relationships between inputs and output: (a) BI versus FPI; (b) Fracture spacing versus FPI; (c) α angle versus FPI; and (d) Field single cutter load versus FPI.

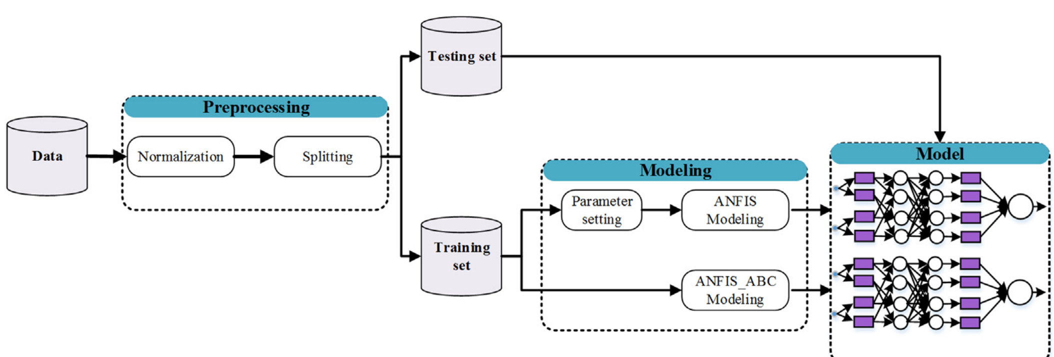


Fig. 5. Experiments framework of the proposed ML technique.

2.3. ANFIS_ABC

OAs can be used in two ways for optimizing parameters of antecedent and conclusion parts in ANFIS model: (1) tune all parameters of the two parts through an OA; and (2) use one independent OA in each layer. We choose the first approach and employ ABC algorithm in both premise and consequence parts.

One of the main superiorities of ABC algorithm over other OAs is that it is not dependent on user's background regarding the definition of hyper-parameters, such as population size, crossover and mutation rates, and inertia weight. The "limit" value is the only control parameter in ABC, unlike most well-known OAs, such as particle swarm optimization, differential evolution, ant colony optimization, and genetic algorithm that need different control parameters. When applying OAs in ANFIS, performance of the ANFIS model is affected by OA-dependent parameters. Appropriate adjustment of the parameters directly influences the final prediction model. Some parameters (e.g. population size) are common to all OAs, while some are not. For example, crossover probability and mutation probability are two parameters in the genetic algorithm (Telikani et al., 2020b). Inertia weight (ω) and acceleration coefficients (c_1 and c_2) are three key parameters in the particle swarm optimization that have impact on the convergence and efficiency. Overall, parameters of OAs introduce different challenges to search process, such as inappropriate exploration, slow convergence, and trapping into the local minima (Alatas and Akin, 2008; Tonnizam Mohamad et al., 2016; Armaghani et al., 2017, 2018b; Xu et al., 2019). In ABC algorithm, only population size and maximum iteration number are set by users.

In addition, ABC algorithm can keep a balance between local and global explorations which are important in any robust search process. In ABC algorithm, the exploitation procedure is applied

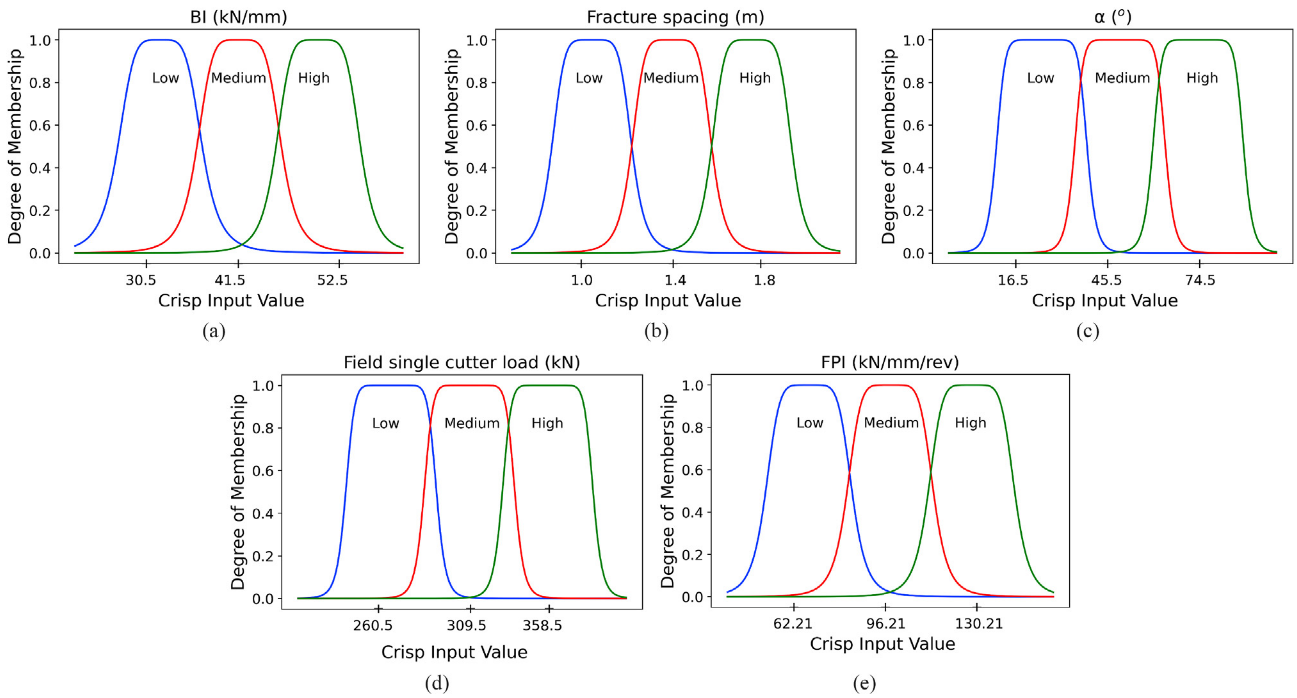


Fig. 6. MFs for variables used in modeling: (a) GbellMF for BI, (b) GbellMF for fracture spacing, (c) GbellMF for α angle, (d) GbellMF for single cutter load, (e) GbellMF for FPI.

using onlooker and employed bees as they abandon exploited food source and randomly select another source, whereas the exploration procedure is conducted through the scout bees since they generate new food source and share the best food source for exploitation (Karaboga and Akay, 2009).

Based on aforementioned benefits, ABC is applied to optimizing both premise and consequence parameters of ANFIS model. Fig. 2 shows the framework of ANFIS_ABC model for FPI prediction. ANFIS_ABC algorithm consists of two main stages. The first stage (i.e. pre-processing step) consists of data normalization, target and independent features determination, and training and testing datasets separation. In the second phase, ABC algorithm is applied in the second step to optimizing the parameters.

In ANFIS_ABC 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. 3.

In order to compute the quality of individuals, root mean square error (RMSE) is used as fitness criterion. To calculate RMSE, the predicted value and its real value are used as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \overline{y_i})}{N}} \tag{10}$$

where y_i and $\overline{y_i}$ are the predicted and actual values, respectively; and N is the size of the dataset. ABC algorithm tries to minimize the RMSE values.

2.4. Database description

In this study, the data obtained from the Queens water tunnel, which is one of the largest projects in New York, was used to predict FPI values. This tunnel was designed as 93 km in length in four different phases. The samples used in this study are collected from the second phase (i.e. the Brooklyn to Queens Section built from 1997 to 2000). This tunnel was excavated with the length and diameter of 7.5 km and 7 m, respectively. This section was constructed at an average depth of 200 m below sea level in western Queens County. The dataset includes different rock types in five categories that were examined carefully before sample preparation and rock testing at the laboratory. If a rock sample deforms that affects its strength and properties, the test result is excluded.

The database gathered for this study consists of more than 150 data points with five parameters, while four are considered as input parameters (i.e. variables of brittleness index (BI), fracture spacing, α angle between the plane of weakness and the TBM driven direction, and field single cutter load) and one (i.e. FPI) as output. Table 2 shows descriptive statistics of the parameters. It is important to emphasize that the database includes intact rock property and rock mass properties together with single disc cutting force (see Table 2). The rock brittleness, which is a combination of rock properties including rock strength, density and porosity, is used as only input. It is found that the brittleness of the rocks ranges from low to extremely high. In addition, Fig. 4 presents the relationships between the inputs and output.

2.5. Evaluation measurements

Different measurements, including RMSE (Eq. (10)), mean absolute error (MAE) (Eq. (11)), R^2 (Eq. (12)), scatter index (SI) (Eq. (13)), and *a*20-*index* (Eq. (14)), are utilized to evaluate the prediction performance of the proposed models. These criteria have been used by many scholars (Zhou et al., 2016; Momeni et al., 2020). The formulae of these measurements are presented as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \overline{y_i}| \tag{11}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_{\mathrm{mean}})^2 - \sum_{i=1}^{n}(y_i - \overline{y_i})^2}{\sum_{i=1}^{n}(y_i - y_{\mathrm{mean}})^2} \tag{12}$$

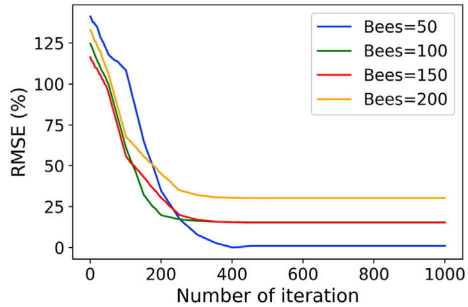


Fig. 7. ANFIS_ABC model performance in terms of various numbers of bees.

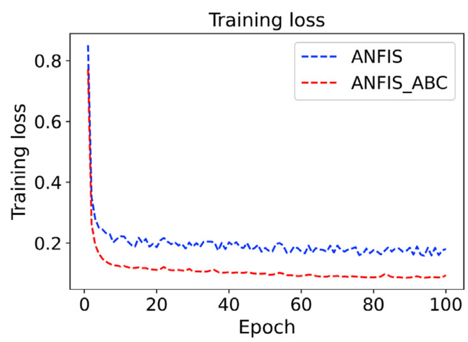


Fig. 8. Average error in terms of the number of epochs.

$$SI = \frac{\sqrt{RSME}}{y_i} \tag{13}$$

$$a20\text{-}index = \frac{m_{20}}{N} \tag{14}$$

where N is the number of samples, and m_{20} is the number of samples with predicted values between 0.8 and 1.2.

3. ML model development and assessment

This section explains the process of carrying out the experiments using ANFIS and ANFIS_ABC predictive models (Fig. 5). In the first step, min-max normalization technique is used to normalize the data. Furthermore, data is divided into the training set (80%, 121 samples) and the testing set (20%, 30 instances). A random process is performed for selection process and the sets are chosen randomly. The ratio of training to testing sets was chosen based on the suggestions available in the literature (Han et al., 2020; Li et al., 2020; Momeni et al., 2020; Zeng et al., 2021). Both ANFIS and ANFIS_ABC models are built using the training set. Once models are generated, the testing set is used to evaluate performance of models by different performance indices (PIs).

3.1. ANFIS modeling

To predict FPI values of TBM using ANFIS, four fuzzy input variables (i.e. BI, fracture spacing, α angle, and field single cutter load) are applied. The generalized bell MF is used which is defined as

$$\mathrm{Bell}(x,a,b,c) = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{15}$$

where x is a one-dimensional (1D) array of values; a, b and c are used to control width, center and slope, respectively. The first input variable is BI. Its MF obtained by the proposed ANFIS model is shown in Fig. 6a. The second input is the fracture spacing. MF obtained by the proposed ANFIS model is depicted in Fig. 6b. The MFs of the third and fourth inputs (i.e. α angle and field single cutter load) are shown in Fig. 6c and d, respectively. The only fuzzy output variable is the FPI value. The fuzzy set for competition radius is demonstrated in Fig. 6e. The ANFIS model with the described structure was constructed to predict the FPI values and its results will be discussed in detail later.

3.2. ANFIS_ABC modeling

Before starting the ANFIS_ABC modeling to estimate the target variable, the ANFIS and ABC parameters must be initialized. In this paper, an improved ANFIS model is proposed for optimizing both precise and consequence layers of the ANFIS model. The number of employed bee (i.e. food sources) and maximum iteration were fixed as 50 and 1000, respectively. It has been proven that ABC algorithm can achieve a high level of performance when the limit value equals *SN* times *D* (Karaboga and Akay, 2009). An early stopping strategy was employed to avoid the overfitting problem, in which the training process stops when the loss value on the validation data is not changed for several epochs.

4. Results and discussion

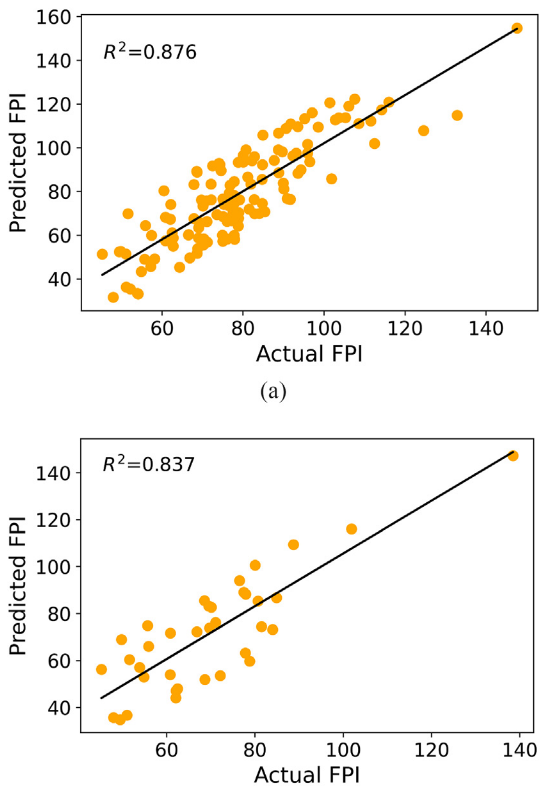
Karaboga and Akay (2009) proved that the optimum limit value for ABC algorithm is *SN* times *D*. When exceeding the limit value for a food source, the bee abandons the source and not exploit anymore.

To assess performance of ANFIS_ABC algorithm in terms of RMSE, a parametric study was conducted on the data in which the number of iterations increases for four different population sizes (i.e. the number of bees). Different predictors were modeled with different bees (i.e. 50, 100, 150, and 200) and iterations. The results of predictive model construction are depicted in Fig. 7, in which RMSE values of models decrease when the number of employed bees increases. However, no significant change in RMSE beyond the maximum cycle number can be observed. This is because the bees are gathered in places where the best answer exists.

Fig. 8 shows the average error on the testing dataset in terms of the number of epochs. This experiment was carried out with 20 epochs in the modeling process. As it can be seen, ANFIS_ABC could yield lower error compared to ANFIS model in predicting FPI. The

Table 3
Performance prediction of the ANFIS-based models to predict FPI.

Model	RMSE		SI		MAE		R^2		*a20-index*	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANFIS	6.17	6.85	0.033	0.0345	2.32	2.63	0.876	0.837	0.8275	0.8196
ANFIS_ABC	3.52	5.19	0.025	0.3	1.73	2.1	0.951	0.901	0.8934	0.862



(a)

(b)

Fig. 9. ANFIS model to estimate FPI: (a) Training set, and (b) Testing set.

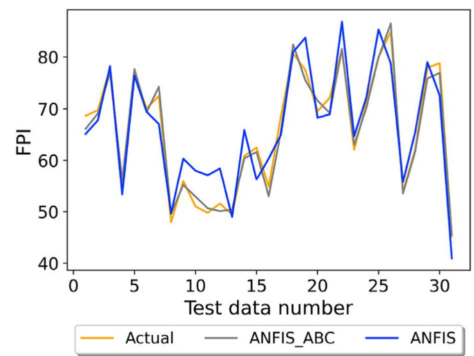


Fig. 11. Plot of measured and predicted FPI values for test stage.

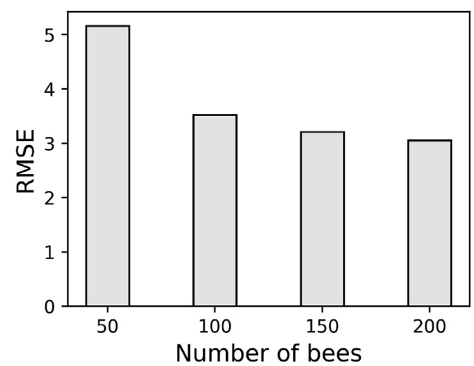
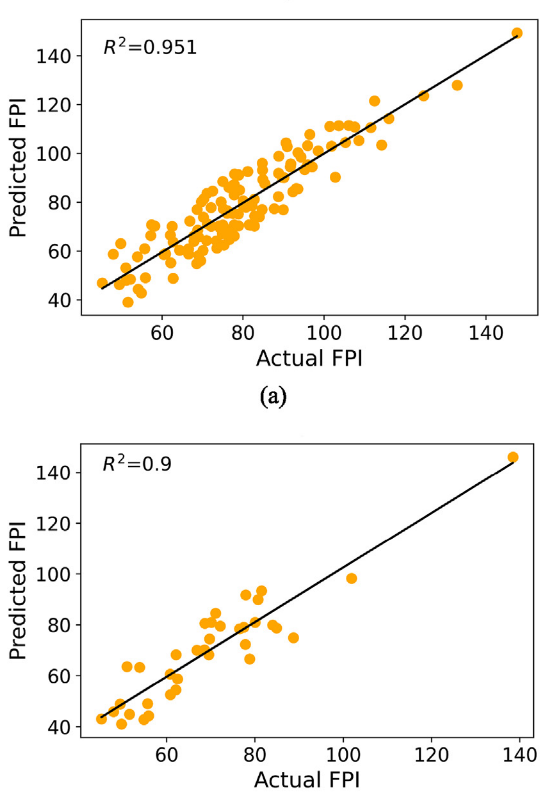


Fig. 12. Assessing performance of ANFIS_ABC model in predicting FPI using testing data in terms of different population size.



(a)

(b)

Fig. 10. ANFIS_ABC model to estimate FPI: (a) Training set, and (b) Testing set.

average error for ANFIS_ABC was about 2.5% lower than that for ANFIS. According to Fig. 8, ANFIS_ABC has a better prediction performance compared to a pre-developed ANFIS model, as ABC is a powerful algorithm on optimizing MF of ANFIS.

Table 3 shows performance of the predictive models in terms of different PIs, including RMSE, SI, MAE, R^2, and *a*20-*index*. According to this table, ANFIS_ABC algorithm yielded a higher agreement between actual and estimated FPI values and lower error compared with those of ANFIS model. Thus, ANFIS_ABC model could provide more accurate prediction results of FPI compared to ANFIS model.

Figs. 9 and 10 show the actual FPI values in comparison with predicted ones by the ANFIS-based models for both train and test stages. According to these figures, the ANFIS_ABC with the R^2 of 0.951 for training data and 0.901 for testing data is the most reliable model to predict FPI values. The ANFIS results were obtained as 0.876 and 0.837 based on R^2, according to its training and testing data, respectively. Form these figures, it is demonstrated that ANFIS_ABC model provides a relatively closer predicted FPI values compared to a pre-developed ANFIS model.

Fig. 11 shows plots between the measured rock FPI (target) and predicted ones (outputs) obtained from ANFIS_ABC and ANFIS

Table 4
Results of ANFIS_ABC for various limit values with $SN = 50$.

PI	l_1	l_2	l_3	l_4
RMSE	5.16	6.1	3.52	10.3
SI	0.03	0.032	0.025	0.042
MAE	2.09	2.32	1.73	2.98
R^2	0.928	0.899	0.951	0.77

models test dataset, respectively. This figure proves that ANFIS_ABC can provide more accurate prediction than ANFIS.

In this study, number of inputs to estimate the PR is reduced but the output and its accuracy are higher compared with those in the literature (Adoko and Yagiz, 2019).

5. Sensitivity analysis

Population size is one of the influencing parameters on the ABC algorithm. In this experiment, four population sizes of 50, 100, 150 and 200 were considered. Fig. 12 shows RMSE values of ANFIS_ABC model with different population sizes. It has been demonstrated that the best bee values were obtained with the population sizes of 150 and 200.

The "limit" parameter regulates the productivity of a scout bee, when the limit value approaches infinity, number of scout bees approaches infinity. Therefore, it is necessary to evaluate how the change of limit value affects the performance of ANFIS_ABC (see Table 4). For this reason, four limit values, including $l_1 = SN(D/4)$, $l_2 = SN(D/2)$, $l_3 = SND$, and $l_4 = 4SND$, were determined with the population size of 200. It can be seen from Table 4 that the highest performance was achieved at l_3, while the lowest performance at l_4. The performance of ANFIS_ABC became worse with an increasing number of scout bees. This is because that the quality of solutions is reduced when the limit value increases, which results in the decline of search ability.

6. Conclusions

In this study, an ANFIS model was improved using ABC algorithm by optimizing parameters and MFs of ANFIS to obtain a minimum prediction error. The data were collected from the Queens water tunnel project that consist of more than 150 samples showing different characteristics of TBM and type of rock mass. Then, the ANFIS_ABC technique was compared with the basic (or pre-developed) ANFIS based on various criteria. According to the results, the ANFIS_ABC algorithm could reduce average errors by 3%. For the proposed ANFIS_ABC model, the values of R^2 and RMSE were 92.6% and 4.35% on average, respectively. It was concluded that the ANFIS_ABC was valuable to estimate the TBM performance with less input variables and higher accuracy in comparison with ANFIS model. Insufficient sample size was one of the main limitations in our study, which may result in overfitting. Hence, authors to address this issue used an early stopping technique. The success of ANFIS_ABC in predicting FPI indicates that this model may be applied to addressing other tunneling and mining engineering problems such as rock strength and deformation predictions. Further investigation can be made in improving performance of parameters optimization using k-fold cross validation in the future, where an ensemble learning on different ANFIS models can be built.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrmge.2021.05.010.

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