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Application of several optimization techniques for estimating TBM advance rate in granitic rocks

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A B S T R A C T

This study aims to develop several optimization techniques for predicting advance rate of tunnel boring machine (TBM) in different weathered zones of granite. For this purpose, extensive field and laboratory studies have been conducted along the 12,649 m of the Pahang – Selangor raw water transfer tunnel in Malaysia. Rock properties consisting of uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), rock mass rating (RMR), rock quality designation (RQD), quartz content (q) and weathered zone as well as machine specifications including thrust force and revolution per minute (RPM) were measured to establish comprehensive datasets for optimization. Accordingly, to estimate the advance rate of TBM, two new hybrid optimization techniques, i.e. an artificial neural network (ANN) combined with both imperialist competitive algorithm (ICA) and particle swarm optimization (PSO), were developed for mechanical tunneling in granitic rocks. Further, the new hybrid optimization techniques were compared and the best one was chosen among them to be used for practice. To evaluate the accuracy of the proposed models for both testing and training datasets, various statistical indices including coefficient of determination (R^2), root mean square error (RMSE) and variance account for (VAF) were utilized herein. The values of R^2, RMSE, and VAF ranged in 0.939–0.961, 0.022–0.036, and 93.899–96.145, respectively, with the PSO-ANN hybrid technique demonstrating the best performance. It is concluded that both the optimization techniques, i.e. PSO-ANN and ICA-ANN, could be utilized for predicting the advance rate of TBMs; however, the PSO-ANN technique is superior.

1. Introduction

Assessment of tunnel boring machine (TBM) advancement is one of the main issues for schedule planning and cost of the project operating in rock mass. Due to this, estimation of TBM performance with actual and corrected parameters would be useful to reduce the cost and risk management of any tunneling projects. Over the last decades, many researchers have developed empirical and theoretical models to predict TBM performance via the penetration rate, advance rate and field penetration index (FPI) (Roxborough and Phillips, 1975; Farmer and Glossop, 1980; Snowdon et al., 1982; Sanio, 1985; Hughes, 1986; Rostami and Ozdemir, 1993; Yagiz, 2002, 2008; Gong and Zhao, 2009). At present, most of researchers agree that TBM advancement could be affected by many factors categorized in three main groups: properties of intact rock and rock mass, and machine specifications.

Both simple and hybrid artificial intelligence (AI) techniques are one of the approaches for solving various geotechnical problems (Singh et al., 2004; Verma and Singh, 2011; Khandelwal and Jahed Armaghani, 2016; Jahed Armaghani et al., 2017a; Koopialipoor et al., 2018a). In order to estimate the TBM performance parameters such as penetration rate, advance rate and FPI, many simple AI techniques, e.g. artificial neural network (ANN), particle swarm optimization (PSO), differential evolution (DE), gray wolf optimizer (GWO), and imperialist competitive algorithm (ICA), as well as several hybrid approaches like hybrid harmony search (HS-BFGS), have been utilized (Alvarez Grima et al., 2000; Benardos and Kaliampakos, 2004; Yagiz et al., 2009; Yagiz and Karahan, 2011;

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Ghasemi et al., 2014; Mahdevari et al., 2014; Jahed Armaghani et al., 2017b).

A part of data of Athens metro tunnel in Greece were used by Benardos and Kaliampakos (2004) to offer an ANN model for predicting the advance rate of TBMs. Using the data of a water tunnel in USA, a support vector regression was modeled by Mahdevari et al. (2014) for predicting the penetration rate. Yagiz and Karahan (2015) developed some optimization techniques, i.e. differential evolutions, HS-BFGS and GWO, to estimate TBM penetration, and they concluded that the HS-BFGS method is more efficient than other methods for predicting TBM penetration based on the properties of intact rock and rock mass. Table 1 summarizes the main researches conducted on prediction of TBM performance via several modeling techniques, together with the inputs and outputs of the proposed models in the literature.

As shown in Table 1, many researchers developed various models to estimate the performance of TBM using optimization techniques. However, their approaches have several constraints including low learning rate and getting trapped in local minima (Lee et al., 1991; Wang et al., 2004; Moayedi and Jahed Armaghani, 2018; Ghaleini et al., 2019). In order to overcome these obstacles, various new optimization algorithms such as genetic algorithm (GA), PSO and ICA are developed. In fact, these introduced algorithms are used to adjust the weight and bias of the created networks. Further, combinations of optimization algorithms and ANN have received great attention due to their capability to solve problems encountered in engineering applications (Momeni et al., 2015; Jahed Armaghani et al., 2016; Mohamad et al., 2017; Khandelwal et al., 2018; Koopialipoor et al., 2018b, 2019a).

The aim of this study is to introduce the hybrid optimization techniques including ICA-ANN and PSO-ANN to estimate the TBM advancement using the data obtained from Pahang – Selangor row water transfer (PSRWT) tunnel project in Malaysia. For this purpose, simple ANN models are developed first, and then two hybrid optimization techniques are introduced. Afterwards, the obtained results from those approaches are compared to choose the best one to estimate the TBM advancement.

2. Case study and data source

The PSRWT tunnel was constructed to transfer water between two states in Malaysia (from Pahang to Selangor). Geological map around the tunnel together with its route is displayed in Fig. 1. A target of transferring 1.89×10^9 L/d of raw water from the Semantan River was planned for this project. The PSRWT tunnel was excavated to cross the Main Range granite of Peninsular Malaysia with an overburden of 100–1400 m. Different weathered zones, from fresh to slightly–moderately weathered, were observed in the PSRWT tunnel. It should be mentioned that in the areas of faults, highly weathered zone was also observed with shear bands and some other local discontinuities. Table 2 presents the rock type and overburden at four different sections of PSRWT tunnel. In this project, various construction sections including 3 TBMs and 4 conventional drill-and-blast were planned to be excavated. The diameter of all the TBMs was 5.23 m, and their specifications are given in Table 3.

3. Input selection criteria for modeling

In general, properties of intact rock and rock mass together with machine specifications are the main factors for any type of mechanical excavation projects. As such, input selection is the most important issue at the beginning of modeling. Many researches have evaluated the input selection criteria for modeling (Mogana et al., 1998; Sapigni et al., 2002; Mogana, 2007; Yagiz, 2008). Yagiz (2002) stated that the intact rock properties including UCS and brittleness are the main parameters that affect the TBM performance, together with the distance between the plane of weakness in the rock mass and the angle α. Benardos and Kaliampakos (2004) indicated that TBM performance relies on RQD, UCS, RMR and weathering degree of rock mass. Several researchers declared that the TBM performance significantly depends on the UCS, BTS, brittleness, RQD and RMR (Benardos and Kaliampakos, 2004; Farrokh et al., 2012), and some other researchers illustrated that the Brazilian tensile strength (BTS) and anisotropy have a great effect on excavatability of rocks such as cutting and boring (Sanio, 1985). Moreover, many studies highlighted the effects of amount of quartz content (q) on the TBM performance (Ozdemir et al., 1978; Barton, 1999). This parameter has been used as a dependent variable in several TBM performance models and classifications (Yavari and Mahdavi, 2005; Eftekhari et al., 2010).

Based on a study conducted by Alvarez Grima et al. (2000), an inverse relationship between UCS and TBM penetration rate was put forward. Their findings suggested that the penetration rate

Table 1
Summary of the research on TBM performance prediction using various techniques.

Output	Input data			Technique	Sources
	Rock mass factor	Rock material factor	Machine factor		
AR	RQD, RMR, k, N, WTS, WZ overburden	UCS	–	ANN	Benardos and Kaliampakos (2004)
PR	DPW, α	UCS, BI	–	ANN	Yagiz et al. (2009)
PR	RMR, RQD, q, rock type	UCS, BTS	RPM, CT, TF	ANN	Eftekhari et al. (2010)
PR	RQD, J_s, J_c	UCS	–	ANN	Gholami et al. (2012)
PR	PSI, α, DPW	UCS, BTS	–	ANN	Salimi and Esmaeili (2013)
PR, AR	CFF	UCS	RPM, D_c, TF	ANN, ANFIS	Alvarez Grima et al. (2000)
PR	WZ, RMR, RQD	UCS, BTS	RPM, TF	PSO-ANN, ICA-ANN	Jahed Armaghani et al. (2017b)
PR	J_s, RQD, RMR, Q, GSI, α	UCS, BTS	–	ANFIS, SVR	Salimi et al. (2016)
PR	DPW, α	BTS, BI, UCS	TF, CT, CP, SE	SVR	Mahdevari et al. (2014)
PR	DPW, α	UCS, BI	–	DE, HS-BFGS, GWO	Yagiz and Karahan (2015)
PR	α, DPW	UCS, PSI	–	ELM	Shao et al. (2013)
PR, AR	CFF	UCS	RPM, D_c, TF	PSO	Yagiz and Karahan (2011)

Note: α is the angle between the plane of weakness and TBM-driven direction; J_c is the joint condition; DPW denotes the distance between the planes of weakness; BI is the rock brittleness; RQD denotes the rock quality designation; CFF represents the core fracture frequency; PR denotes the penetration rate; AR denotes the advance rate; D_c is the cutter diameter; PSI denotes the peak slope index, also referred to as the rock brittleness index; q is the quartz content; k is the permeability; J_s is the joint spacing; SE represents the specific energy; TF is the thrust force; CP is the cutterhead power; RPM is the revolution per minute; CT is the cutterhead torque; ELM is the extreme learning machine; ANFIS denotes the adaptive neuro-fuzzy inference system; SVR denotes the support vector regression; N is the overload factor; Q is the quality system; GSI denotes the geological strength index; RMR denotes the rock mass rating; WTS is the water table surface; WZ denotes the weathered zone; UCS is the uniaxial compressive strength; BTS is the Brazilian tensile strength.

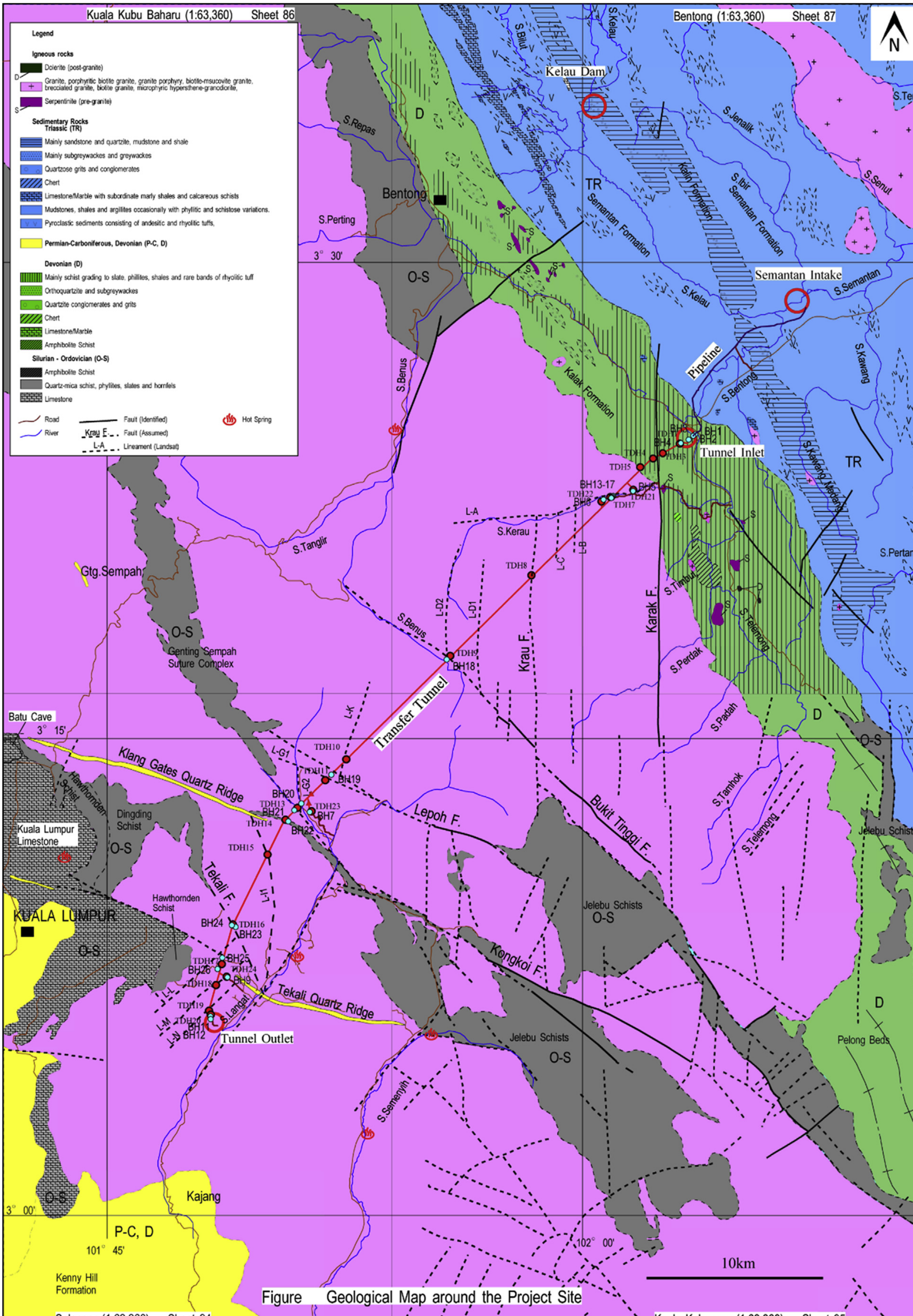

Fig. 1. Geological map around the tunnel together with its route.

Table 2
Four main zones of PSRWT tunnel project.

Zone	Rock type/property	Overburden
Zone 1: Chainage of 0.86–3.8 km	Meta-sedimentary rocks	Maximum cover = 240 m
Zone 2: Chainage of 3.8–12.5 km	Granite	Maximum cover = 483 m, and minimum cover = 33 m
Zone 3: Chainage of 12.5–27 km	Granite beneath Main Range	Maximum cover = 1390 m, and minimum cover = 564 m at a stream crossing
Zone 4: Chainage of 27–44.6 km	Eastern intensively weathered flank of Main Range, including short schist section at about 32–32.5 km	Maximum cover = 485 m, and minimum cover = 65 m

Table 3
Specifications of TBMs operated for PSRWT tunnel project.

Description		Specification	Description		Specification
TBM diameter and type		5.2 m, open type TBM	Number of backup trailer		20
Maximum stroke		1.8 m	Length	TBM	27 m
Power		AC 11,000 V, 3 phase, 50 Hz		Backup	178 m
Cutterhead output		2205 kW		Total	205 m
Cutter disc diameter		19 inch (483 mm)	Mass	TBM	250 t
Number of cutters	Single cutter	27 (19 inches in diameter, cutter)		Backup	170 t
	Center cutter	8 (17 inches in diameter, cutter)		Total	420 t
	Total	35 Cutters	Transformer		3400 kVA (11,000–660 V)
Maximum load (cutter)		312 kN			1700 kVA (11,000–380 V)
Thrust		14,000 kN (=3500 kN × 4)	Stroke of jacks to tow backup trailer		2 m
Maximum cutter torque		3504 kN m	Belt conveyor	Width	914 mm
Cutterhead rotation speed		0–13.2 rpm		Capacity	895 m^3/h

decreases with the decrease in RPM, but increases with UCS. Farrokh et al. (2012) declared that rock properties including rock type, RQD, UCS, machine specifications such as RPM and normal force, and tunnel diameter are the main factors that influence the TBM performance. Mahdevari et al. (2014) used the properties of both intact rock and rock mass such as strength, brittleness and feature of discontinuities as well as machine specifications including cutterhead torque, thrust, cutterhead power and specific energy to assess the TBM performance; however, the model has so many inputs which are not easy to be collected in the early stage of the project. Therefore, the models introduced so far have some advantages and disadvantages in comparison with each other. But it should be mentioned that every model should have reliable database, relevant inputs and accurate outputs to solve practical engineering problems.

In this study, in order to establish the datasets, the PSRWT tunnel excavated in Malaysia was studied by performing the field and laboratory works. As a result, a comprehensive database comprising the properties of rocks and machine in various weathered zones (i.e. fresh, slightly and moderately weathered) was built. The database has 1286 datasets that are composed of rock properties, machine specifications and TBM performance parameters. Except for the well-known rock properties including UCS, RQD, *q*, BTS and RMR, some rock mass properties such as weathering degree, joint conditions, and in situ strength and groundwater conditions were examined in the field and then quantified. Further, TBM parameters such as stroke speed, cutter load, thrust, RPM, penetration rate, and cutterhead torque were analyzed and recorded in the database. In the laboratory, intact rock tests including Schmidt hammer BTS, UCS, point load strength, and P-wave velocity tests were conducted using 154 samples of block gathered from the tunnel face in accordance with the International Society for Rock Mechanics and Rock Engineering (ISRM) standards (Ulusay and Hudson, 2007). Rock material properties (UCS and BTS), rock mass properties (*q*, RQD, RMR and weathered zones of the rock mass) and machine specifications (thrust and RPM) were set as inputs to develop predictive techniques.

Various rock and machine properties could be used for modeling, depending on the range of the dataset and the quantified parameters. In this study, 8 input parameters including measured properties of intact rock and rock mass together with machine specifications were selected and utilized for developing hybrid models, i.e. PSO-ANN and ICA-ANN herein.

It should be noted that this is one of the comprehensive databases including TBM specifications, rock mass properties as well as intact rock properties for the aim of study, as summarized in Table 4.

4. Intelligent methods for predicting TBM advance rate

Many investigations indicate the effects of optimization algorithms such as GA, ICA and PSO on enhancing the ANN performance. They were utilized to adjust the bias and weight of ANN model. In the present study, ICA and PSO were selected and used to

Table 4
Basic statistical description and the range of dataset used for modeling.

Data	Abbreviation	Unit	Data type	Minimum	Maximum	Mean
Rock quality designation	RQD	%	Input	6.25	95	44.15
Uniaxial compressive strength	UCS	MPa	Input	40	185	107.45
Rock mass rating	RMR	–	Input	44	95	64.73
Brazilian tensile strength	BTS	MPa	Input	4.69	15.7	8.43
Quartz content	Q	%	Input	30.1	60.2	36.62
Weathered zone	WZ	–	Input	1	3	1.7
Thrust force per cutter	TF	kN	Input	80.6	565.9	321.52
Revolution per minute	RPM	rev/min	Input	4.08	12	8.84
Advance rate	AR	m/h	Output	0.017	5	1.09

optimize the bias and weight of ANN. In fact, the above-mentioned optimization algorithms are considered to determine the global minimum. Using PSO and ICA, it is expected that the performance prediction of ANN may be increased significantly. In this section, after explaining the structures of the developed models, namely ANN, PSO and ICA, their modeling process for predicting the advance rate of TBM will be given. In order to develop simple and hybrid optimization models, Matlab version 7.14.0.739 was utilized herein (Demuth et al., 2009).

4.1. Artificial neural network

Fundamentally, an ANN refers to as a mathematical model that simulates reasoning operation in the human brain. In fact, the ANN simulates one or more output(s) in a way that identifies the complicated relations among variables. An ANN model is basically designed based on three principal elements: transfer function, connection pattern, and learning rule (Simpson, 1990). These elements depending on the type of problem are employed to train the network by modifying its weight (Hasanipanah et al., 2018; Koopialipoor et al., 2019b). One of the most frequently used feedforward neural networks is multilayer perceptron (MLP) that comprises three different types of consecutive layers of nodes. These layers include an input layer, one or more mid-layers, and an output layer. Each of them contains a number of nodes/neurons with specific mathematical relationships. The function of input layer is to receive input signals from the entrance of system and then transmit them to the succeeding layers. The neurons of middle (hidden) layer are able to detect the underlying characteristics of the input patterns. Subsequently, these characteristics allow the output layer to find the output pattern using output neurons (Bounds et al., 1998; Koopialipoor et al., 2018c).

Numerous variants of algorithms have been developed to train the neural networks during an iterative process. The backpropagation (BP) technique is considered as the most common method among the MLP learning algorithms (Basheer and Hajmeer, 2000; Gordan et al., 2018). In this technique, the data of input fed directly into the input layer are exchanged between the neurons of different layers until an output is produced. The net weighted input received by each neuron is calculated based on the following formula:

$$X = \sum_{i=1}^{n} X_i W_i - \theta \tag{1}$$

where n represents the data number of inputs; X_i and W_i are the input signal and weight for the ith node, respectively; and θ represents the applied threshold to the neurons. Data of net input are transmitted through a specific transfer function. Technically, this process is referred to as training procedure. Subsequently, by comparing the actual outputs with the predicted outputs, the output error is computed (Dreyfus, 2005). Finally, the produced error is propagated through the network in a reverse order for the purpose of fine-tuning the individual weights. This stage is termed as backward pass. The weight updating continues till the error measure is reduced to a certain level that can be defined as the mean square error (MSE) (Simpson, 1990). It should be noted that an insufficient number of datasets could lead to the phenomenon of overfitting during the training process of an ANN model (Dreyfus, 2005).

In order to develop the ANN model, available data utilized for modeling should be normalized prior to its usage (Khamesi et al., 2015). This is achieved by the following equation:

$$X_{norm} = (X - X_{min})/(X_{max} - X_{min}) \tag{2}$$

where X_{norm}, X_{max} and X_{min} are the normalized, maximum and minimum values of X, respectively. All established databases should be divided into two categories, i.e. training and testing. This must be done for developing and evaluating the created networks. Swingler (1996) recommended a value of 20% of whole data for testing purposes. Therefore, 80% and 20% of 1286 datasets were used for training and testing datasets, respectively. In the next step of ANN modeling, the Levenberg–Marquardt (LM) algorithm was selected to create all ANN models. Based on the previous studies, several researchers noted the proficiency of the LM algorithm which can approximate problems of geotechnical engineering (e.g. Ornek et al., 2012). In addition, as mentioned by many researchers (e.g. Hornik et al., 1989), the created ANN with a hidden layer can assess almost all problems. Therefore, in this study, all networks were created using one hidden layer.

For designed number of hidden nodes (N_h), Sonmez and Gokceoglu (2008) mentioned that it has a deep impact on the performance prediction of an ANN model. Several investigators introduced equations for determination of N_h (Hecht-Nielsen, 1987; Ripley, 1993; Masters, 1994; Paola, 1994; Wang, 1994; Kaastra and Boyd, 1996; Kanellopoulas and Wilkinson, 1997). Among them, input number of $2N_i + 1$ is considered as the upper limitation for N_h, where N_i is the input number of the network. Accordingly, it seems that N_h range of 1–15 can approximate the results of the advance rate in this research considering the trial-and-error method. Hence, 15 ANN models with N_h ranging from 1 to 15 were constructed and their performance predictions were checked using the average values of coefficient of determination (R^2), as shown in Fig. 2. It is worth mentioning that the results presented in Fig. 2 are the average values of 5 runs of training and testing of ANN models for each N_h. It was found that an ANN predictive model with $N_h = 12$ obtains the best performance compared with the other created models. The average R^2 values of 0.745 and 0.678 are achieved for training and testing sections of model No. 12, respectively. Hence, architecture of $8 \times 12 \times 1$ was chosen to predict the advance rate by using ANN. More information about the features of the best created model of ANN (among 5 runs) is given later.

4.2. Particle swarm optimization

Kennedy and Eberhart (1995) developed the PSO as one of the optimization algorithms. This algorithm is based on the behavior of some animals like fish and bird schooling in nature (Yang, 2010;

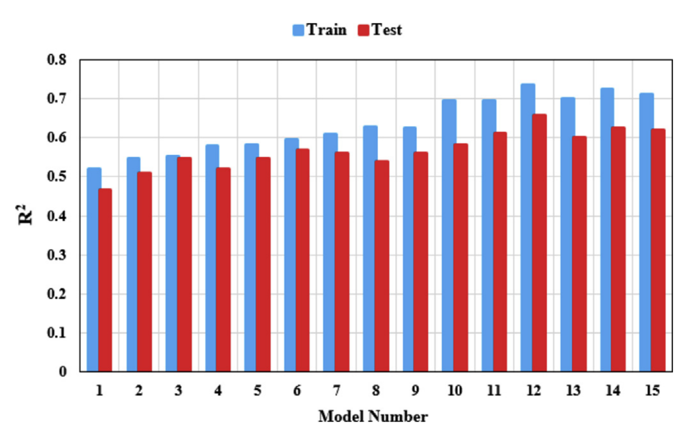

Fig. 2. The average R^2 values of training and testing data for predicting TBM advance rate.

Brownlee, 2011). The main purpose of PSO algorithm is to propagate particles in the desired function space. In this way, these particles are placed at the optimal points of this space. In this algorithm, the particles have a tendency of random movement. These particles find the best global (p^*) and local (x_i^*) positions and move towards them. Thus, by comparing the locations, the best location is determined for the particles. This is done at time t for a number of particles. Finally, they find the best solution for the stopping criterion. Fig. 3 shows a view of the particle motion in the PSO, where x_i^* is the current best and $p^* \approx \min\{f(x_i)\}$ is the global best for particle i ($i = 1, 2, \cdots, n$). It is important to mention that there are several factors that influence the PSO, i.e. swarm size or number of particle, velocity coefficients (C_1 and C_2), and inertia weight (w). Further information related to the application of PSO algorithm to real problem could be found in the literature (Jahed Armaghani et al., 2017b).

The PSO is one of the common optimization techniques used for estimating the unknowns for solving optimization and engineering problems. Due to that, the combined PSO with ANN technique is introduced to estimate the TBM advancement herein. There are several effective parameters for evaluating the performance of PSO-ANN model, such as number of particle or swarm size. A parametric investigation was performed on swarm size using a trial-and-error procedure. According to the obtained results, swarm size of 350 shows the lowest MSE (RMSE), hence this value was selected for the hybrid system. The second step of modeling is related to the identification of termination criterion, which is considered as the maximum number of iteration (I_{Max}) in this study. To determine I_{Max}, many values of swarm were considered to train the hybrid PSO-ANN system, as displayed in Fig. 4. It should be noted that evaluation of the system was based on the RMSE results. As shown in Fig. 4, after 450 iterations, no significant changes were observed for all the particles. Therefore, I_{Max} of 450 was selected in the modeling design of this study for prediction of TBM advance rate.

In the next step of modeling, proper values of C_1 and C_2 should be designed. Various combinations of C_1 and C_2 such as $C_1 = C_2 = 2$, and $C_1 = 1.333$ and $C_2 = 2.667$ were previously used by the researchers. It seems that these values need to be determined using another parametric study based on the RMSE results. After conducting relevant analyses, it was found that $C_1 = 1.333$ and $C_2 = 2.667$ indicate the lowest system error. Thus, the obtained values of system were applied to the design of the hybrid PSO-ANN model. Determining the inertia weight is the next stage of PSO-ANN modeling. Based on the literature review, 4 values of inertia weight, i.e. 0.25, 0.5. 0.75 and 1, were selected to conduct another sensitivity analysis. The obtained results showed that the best network performance can be obtained using $w = 0.75$, thus this value was considered for the system modeling. Finally, 5 PSO-ANN models were constructed and/or trained considering 5 different sets of training and testing datasets and using the obtained values of PSO parameters. The constructed models and relevant parameters together with other modeling approaches are discussed later in this study.

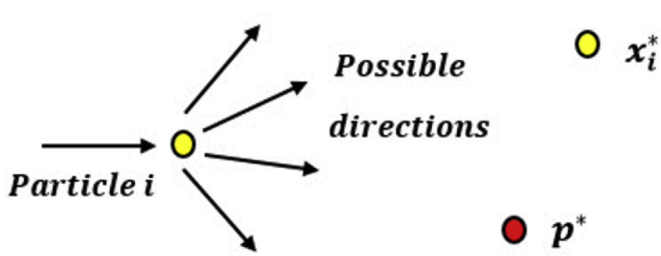

Fig. 3. A view of the particle motion in the algorithm of PSO.

4.3. Imperialist competitive algorithm

ICA used herein is another optimization algorithm introduced by Atashpaz-Gargari and Lucas (2007). This algorithm works based on a global search population technique. In ICA, in the initial step, there are several numbers of countries considered as random initial populations. The system is started by creating a random number of countries ($N_{country}$). In the second stage, a specified number of countries with conditions like the lowest costs or lowest MSE or RMSE are selected. They are deemed as the most powerful countries or the imperialists (N_{imp}) and the remaining countries in the system are named as colonies (N_{col}). The next stage is related to the distribution of the colonies among empires. This distribution will be performed according to the empires' initial powers.

In ICA technique, the most powerful imperialists, i.e. individuals with the least costs, have the highest number of colonies. Similar to other optimization algorithms, there are three operators in ICA, namely, assimilation, revolution and competition. An attraction from the colonies to the imperialists happens through the assimilation operator. Nevertheless, several sudden movements in the situations of the countries occur during the revolution operator. Therefore, there is a possibility for a colony during assimilation and revolution operators to reach/control a more stable condition. During competition, all imperialists try to adopt more colonies as reality. Under these conditions, all empires are trying to run the colonies of other empires. At the end of analysis, the weak empires are gradually going to collapse and subsequently, the more powerful ones are going to increase their power with colonies. The mentioned process is continued until all weak empires collapse or the system meets specific termination criteria (e.g. RMSE, MSE or maximum number of decade). More information about ICA technique could be found in the literature (Atashpaz-Gargari et al., 2008; Taghavifar et al., 2013; Hajihassani et al., 2015; Jahed Armaghani et al., 2017b).

As noted previously, three factors, i.e. number of country $N_{country}$, number of empire N_{imp}, and number of decade N_{decade}, are the most important parameters for ICA model. Various values of $N_{country}$ have been utilized to approximate problems of geotechnical engineering. Ahmadi et al. (2013), Marto el al. (2014) and Hajihassani et al. (2015) proposed values of 40, 56 and 135 for $N_{country}$, respectively. According to their findings, it is shown that a parametric study is needed to find a suitable value of $N_{country}$. Therefore, a series of ICA-ANN analyses was conducted using various $N_{country}$ values ranging from 25 to 500. In these models, $N_{decade} = 200$ and $N_{imp} = 10$ were utilized. The obtained results showed that $N_{country} = 300$ receives the best performance compared with the other models. Therefore, in this stage, the optimum $N_{country}$ value was selected as 300 for modeling of TBM advance rate.

In the next stage of ICA-ANN, to find the optimum performance of N_{imp}, there is a need to carry out another parametric study. Therefore, several values of N_{imp} in the range of 5–65 were used to distinguish the best performance of N_{imp} for modeling of TBM advance rate. Based on the obtained findings, $N_{imp} = 30$ has the best performance among the models based on the RMSE results. Therefore, the optimum N_{imp} value was determined as 30. In the next step, the optimal value of N_{decade} should be determined for designing a perfect ICA model through another parametric study. For this purpose, N_{decade} was set as 1000 in this research. Fig. 5 displays the network results of using different values of N_{decade} for estimating TBM advance rate. As can be seen, there are no significant changes in the results after $N_{decade} = 800$. Hence, the optimum N_{decade} value was selected as 800 for modeling of TBM advance rate. In the final stage of modeling with the hybrid ICA-ANN, considering the same 5 training and testing datasets in the

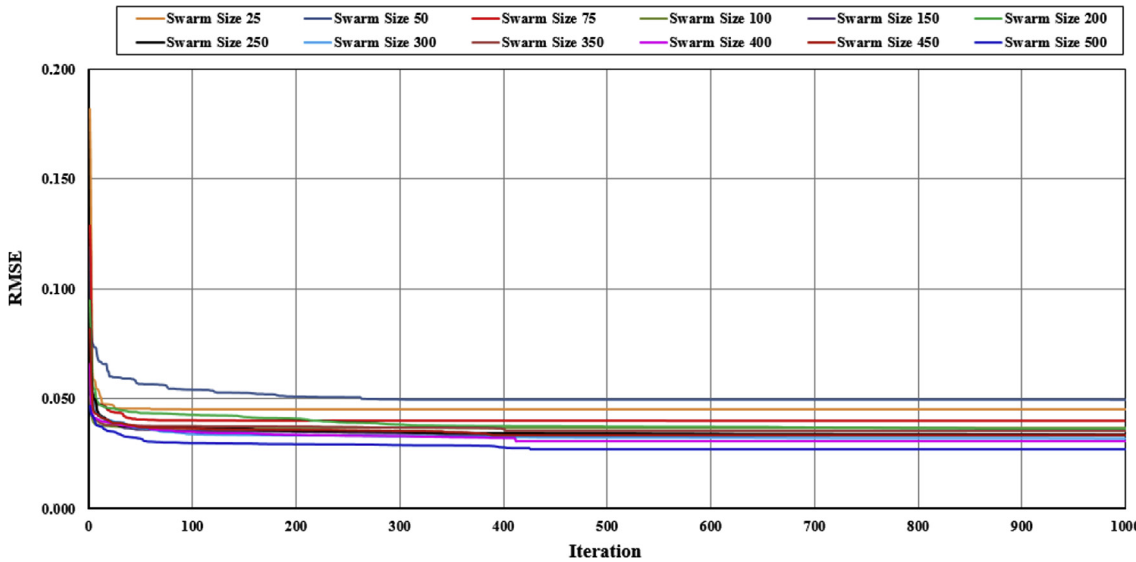

Fig. 4. Effect of the number of iteration on the hybrid PSO-ANN system for modeling of TBM advance rate.

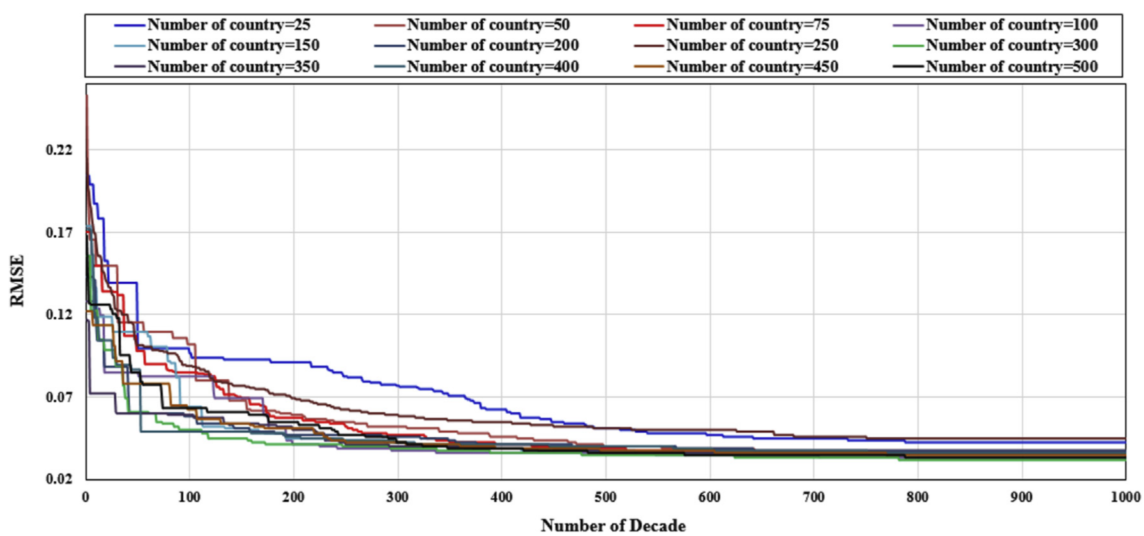

Fig. 5. Effect of the number of decade on the modeling of TBM advance rate.

previous section, the suggested ANN architecture ($8 \times 12 \times 1$) and the obtained ICA-ANN parameters, 5 ICA-ANN models were created and the best performance among them was selected. Obtained results and output are discussed in Section 5 by comparing the models with each other.

5. Model evaluation

In this section, the above-mentioned models are compared with each other to choose the most efficient one among them. At the last stage of developing models including ANN and hybrid PSO-ANN and ICA-ANN, 5 training sets for each model were run to predict the advance rate of TBM. Examining the results obtained from these models has been performed according to some performance indices, based on the statistical parameters including RMSE, R^2 and variance account for (VAF) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y-y')^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y-y')^2}{\sum_{i=1}^{N}(y-\tilde{y})^2} \tag{4}$$

Table 5
The results of performance indices obtained by the ANN, PSO-ANN and ICA-ANN models.

Model	Train/test	R^2	RMSE	VAF	Rating for R^2	Rating for RMSE	Rating for VAF	Rank value
ANN	Train 1	0.749	0.063	74.853	3	3	3	9
	Train 2	0.751	0.062	75.092	4	4	4	12
	Train 3	0.739	0.065	73.813	2	2	1	5
	Train 4	0.754	0.061	75.445	5	5	5	15
	Train 5	0.738	0.065	73.824	1	2	2	5
	Test 1	0.694	0.072	69.416	2	3	2	7
	Test 2	0.679	0.075	66.856	1	2	1	4
	Test 3	0.713	0.068	71.295	5	5	5	15
	Test 4	0.706	0.069	70.566	4	4	4	12
	Test 5	0.701	0.069	70.151	3	4	3	10
PSO-ANN	Train 1	0.958	0.028	95.832	4	3	4	11
	Train 2	0.961	0.023	96.089	5	5	5	15
	Train 3	0.952	0.030	95.207	2	2	2	6
	Train 4	0.949	0.031	94.981	1	1	1	3
	Train 5	0.957	0.027	95.779	3	4	3	10
	Test 1	0.961	0.022	96.145	4	5	4	13
	Test 2	0.957	0.027	95.655	2	3	2	7
	Test 3	0.955	0.028	95.535	1	2	1	4
	Test 4	0.963	0.022	96.349	5	5	5	15
	Test 5	0.959	0.025	95.948	3	4	3	10
ICA-ANN	Train 1	0.945	0.031	94.544	3	4	3	10
	Train 2	0.941	0.033	94.078	2	3	2	7
	Train 3	0.948	0.029	94.849	5	5	5	15
	Train 4	0.939	0.036	93.899	1	2	1	4
	Train 5	0.946	0.031	94.581	4	4	4	12
	Test 1	0.944	0.032	94.385	3	3	3	9
	Test 2	0.939	0.035	93.956	1	2	1	4
	Test 3	0.951	0.026	95.181	4	5	4	13
	Test 4	0.943	0.031	94.350	2	4	2	8
	Test 5	0.954	0.026	95.456	5	5	5	15

$$VAF = \left[1 - \frac{\mathrm{var}(y - y')}{\mathrm{var}(y)}\right] \times 100\% \tag{5}$$

where y, y' and $\tilde{y}$ are the target, output and mean of the variable y, respectively; and N is the total number of datasets. To obtain a network model that is theoretically perfect, RMSE, R^2 and VAF should be 0, 1 and 100, respectively.

Table 5 presents the obtained results of R^2, RMSE and VAF for the mentioned 15 AI models. As can be seen in this table, the obtained results of all the performance indices are very close to each other; therefore, it seems not easy to decide the best AI model. In order to solve the matter, a method of ranking proposed by Zorlu et al. (2008) was utilized herein. Based on this technique, the performance indices (R^2, VAF or RMSE) of each model are obtained and then grouped, as indicated in Table 5. After then, the best performance index was allocated the highest value for determining the best accurate model. In this section, R^2 values of 0.958, 0.961, 0.952, 0.949 and 0.957 were obtained for training datasets 1–5 of PSO-

Table 6
Results of the total rank for all the predictive models.

Model	Model No.	Total rank
ANN	1	16
	2	16
	3	20
	4	27
	5	15
PSO-ANN	1	24
	2	22
	3	10
	4	18
	5	20
ICA-ANN	1	19
	2	11
	3	28
	4	12
	5	27

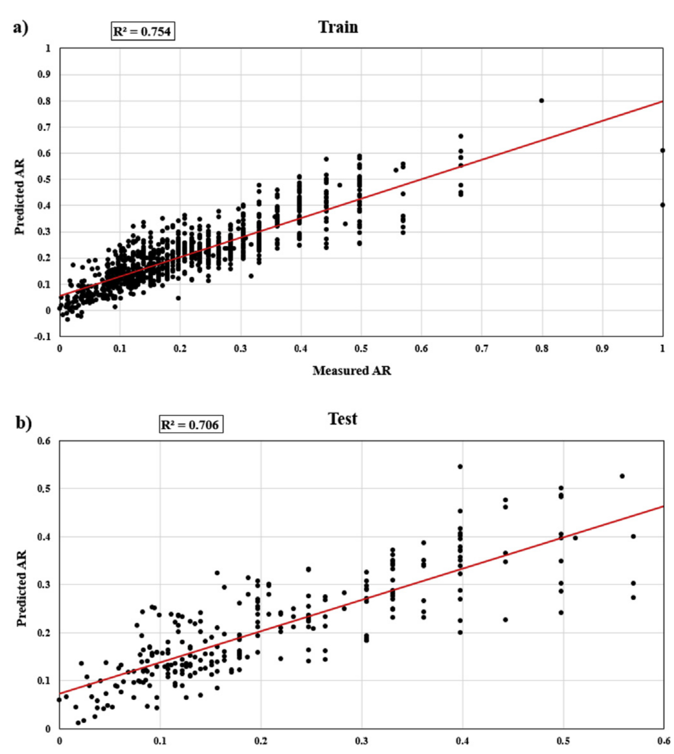

Fig. 6. The best results of ANN model for prediction of TBM advance rate.

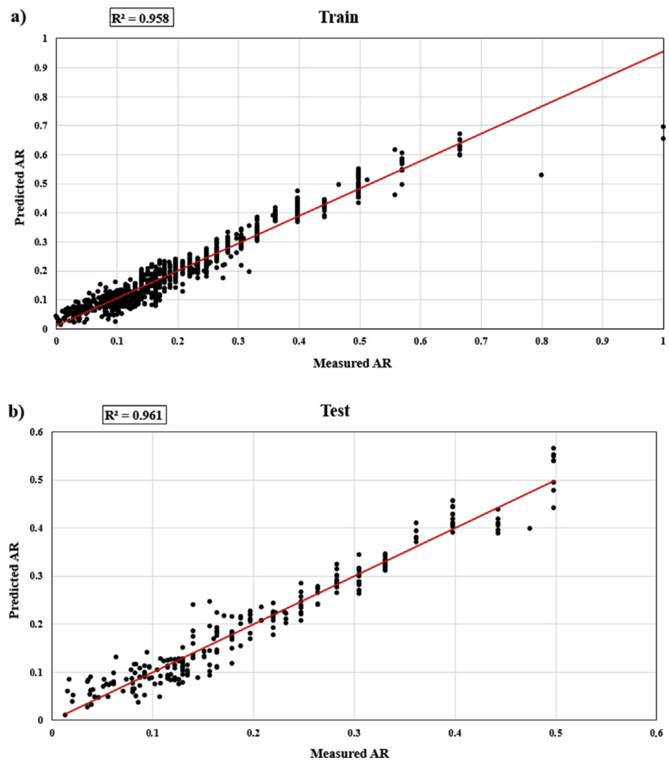

Fig. 7. The best results of PSO-ANN model for prediction of TBM advance rate.

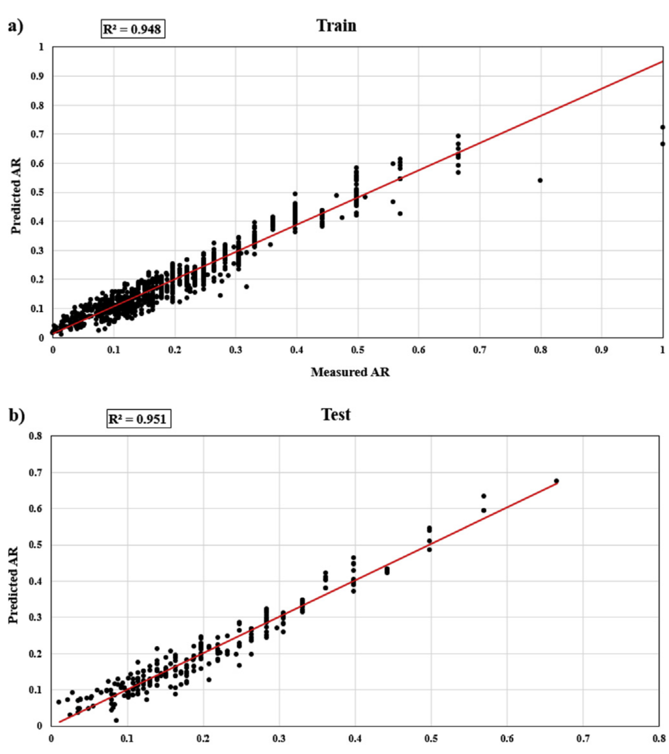

Fig. 8. The best results of ICA-ANN model for prediction of TBM advance rate.

ANN models, and values of 4, 5, 2, 1 and 3 were allocated for their ranks, respectively. Additionally, this process was repeated for other indices and also for testing datasets. Afterwards, for each AI model, the ratings of the performance indices for both training and testing datasets were summed up (see the total rank in Table 6). Based on the results of the total rank, ANN dataset No. 4, PSO-ANN dataset No. 1 and ICA-ANN dataset No. 3 with the total rank values of 27, 24 and 28, respectively, indicate the highest performance capacity for the modeling techniques. The results revealed that by developing hybrid models, i.e. PSO-ANN and ICA-ANN, the performance capacity of the system can be increased based on R^2, from about 0.7 (for pre-developed ANN) to about 0.95 (for hybrid models). Results of ANN (with R^2, RMSE and VAF values of 0.754, 0.061 and 75.445 for training, and 0.706, 0.069 and 70.566 for testing, respectively), PSO-ANN (with R^2, RMSE and VAF values of 0.958, 0.028 and 95.832 for training, and 0.961, 0.022 and 96.145 for testing, respectively) and ICA-ANN (with R^2, RMSE and VAF values of 0.948, 0.029 and 94.849 for training, and 0.951, 0.026 and 95.181 for testing, respectively) are obtained for the applied models of this study.

The best relationships between the measured and predicted TBM advance rate using the developed ANN as well as hybrid predictive models are displayed in Figs. 6–8. The results revealed that the presented hybrid models (PSO-ANN and ICA-ANN) are better than the pre-developed ANN model. Nevertheless, when both training and testing datasets are considered, R^2 values of 0.958 and 0.961, and 0.948 and 0.951 for PSO-ANN and ICA-ANN techniques, respectively, demonstrate that the PSO-ANN model can propose slightly higher capacity of network for prediction of TBM advance rate in comparison to the other developed hybrid model.

6. Conclusions

In this study, three intelligent models, i.e. pre-developed ANN, hybrid PSO-ANN and hybrid ICA-ANN, were utilized to estimate the advance rate of TBMs. For this purpose, the PSRWT tunnel project in Malaysia was studied not only in field but also in laboratory by conducting rock testing program. Established datasets including properties of intact rock and rock mass together with machine parameters were utilized. In these datasets, 8 model inputs were set, i.e. UCS and BTS of material property category, RQD, q, RMR and weathered zone of rock mass property category, and also thrust and RPM of machine characteristics category. After conducting the modeling procedures of predictive models, the best results of ANN, PSO-ANN and ICA-ANN models for prediction of TBM advance rate were selected based on the obtained performance indices. A comparison with the previously developed intelligent models for TBM performance prediction showed that the proposed PSO-ANN and ICA-ANN models having high degree of accuracy and efficiency can be used as new techniques for prediction of TBM performance. However, the hybrid PSO-ANN model provides slightly higher performance capacity of estimating the advance rate in comparison with the ICA-ANN model. The R^2 values of 0.958 and 0.961 and 0.948 and 0.951 and VAF values of 95.832 and 96.145 and 94.849 and 95.181 were obtained for training and testing datasets of PSO-ANN and ICA-ANN models, respectively. It is concluded that the developed PSO-ANN model is superior compared to the ICA-ANN; however, the results obtained from the developed models are valid for similar rock types and the same model inputs with presented ranges of dataset. It is important to mention that the hybrid intelligent systems introduced in this study could be considered as new models in the field of TBM advance rate prediction.

Conflicts of interest

The authors wish to confirm that there are no known conflicts of interest associated with this publication and there has been no

significant financial support for this work that could have influenced its outcome.

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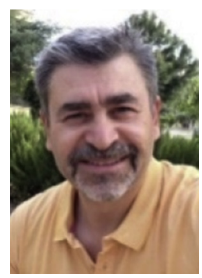

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