Geomechanics and Engineering, *Vol. 31, No. 4 (2022) 339-352*
https://doi.org/10.12989/gae.2022.31.4.339

Slope stability prediction using ANFIS models optimized with metaheuristic science

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(*Received July 20, 2021, Revised October 20, 2022, Accepted October 28, 2022*)

Abstract. Studying slope stability is an important branch of civil engineering. In this way, engineers have employed machine learning models, due to their high efficiency in complex calculations. This paper examines the robustness of various novel optimization schemes, namely equilibrium optimizer (EO), Harris hawks optimization (HHO), water cycle algorithm (WCA), biogeography-based optimization (BBO), dragonfly algorithm (DA), grey wolf optimization (GWO), and teaching learning-based optimization (TLBO) for enhancing the performance of adaptive neuro-fuzzy inference system (ANFIS) in slope stability prediction. The hybrid models estimate the factor of safety (F_S) of a cohesive soil-footing system. The role of these algorithms lies in finding the optimal parameters of the membership function in the fuzzy system. By examining the convergence proceeding of the proposed hybrids, the best population sizes are selected, and the corresponding results are compared to the typical ANFIS. Accuracy assessments via root mean square error, mean absolute error, mean absolute percentage error, and Pearson correlation coefficient showed that all models can reliably understand and reproduce the F_S behavior. Moreover, applying the WCA, EO, GWO, and TLBO resulted in reducing both learning and prediction error of the ANFIS. Also, an efficiency comparison demonstrated the WCA-ANFIS as the most accurate hybrid, while the GWO-ANFIS was the fastest promising model. Overall, the findings of this research professed the suitability of improved intelligent models for practical slope stability evaluations.

Keywords: metaheuristic optimizers; neuro-fuzzy model; optimization; safety engineering; slope stability

1. Introduction

Exploring slope stability is an essential step in many civil engineering projects (Li *et al.* 2015, Xie *et al.* 2021b). It can be an effective way of reducing enormous damages caused by slope failures (Singh *et al.* 2020). So far, many attempts have been conducted for approximating the factor of safety (F_S) of different slopes, but due to the effect of many parameters on the F_S (Cho 2007), they have led to complicated calculations. For this reason, many scholars have suggested employing indirect evaluative models (Ji *et al.* 2017).

Going more profoundly in recent advances, many innovative approaches/tools have been used for improving the design and calculation in different domains (Yan *et al.* 2019, Zhou *et al.* 2021b, Dai *et al.* 2022, Gu *et al.* 2022).

This improvement has been widely reported for structural systems (Zhao *et al.* 2020a, Huang *et al.* 2021a, Ghasemi *et al.* 2022) and components (Huang *et al.* 2021b, Wei *et al.* 2021, Zhao *et al.* 2021a), road construction and mining (Guo *et al.* 2022, Zhu *et al.* 2022), geological investigations (Jiang *et al.* 2021, Liu *et al.* 2022, Xu *et al.* 2022), material strength (Wu *et al.* 2022, Yuan *et al.* 2022), remote sensing (Ye *et al.* 2020a, Liu *et al.* 2021, Wang *et al.* 2021) and earth observation (Zhou *et al.* 2021a, Li *et al.* 2022a, Li *et al.* 2022b), environmental issues like natural disasters (Zhang *et al.* 2020b, Mehrabi 2021) and dam-related analysis (Chen *et al.* 2022, Yin *et al.* 2022).

Machine learning tools have attracted huge attention in classification and regression analysis (Zhang *et al.* 2019, Li *et al.* 2021, Zheng *et al.* 2021, Zhan *et al.* 2022). Engineering problems and particularly, the safety of slope and landslide (Xie *et al.* 2021c, Xie *et al.* 2021d) have been widely benefitted from the presence of various artificial intelligence models (Foong *et al.* 2021, Zhao *et al.* 2022).

Zhao and Wang (2022) used the DBSCAN algorithm to improve the calculation efficiency of subset simulation. The computational capability of their method was investigated through three numerical examples, and the results indicate that the proposed method is an efficient tool for reliability

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http://www.techno-press.org/?journal=gae&subpage=7
ISSN: 2005-307X (Print), 2092-6219 (Online)

estimation. Bui *et al.* (2019) presented a successful use of artificial neural network (ANN) for approximating the F_S after a finite element analysis. The large correlation between the F_S obtained from finite element and the ANN results proved the suitability of this model. Fattahi and Ilghani (2020) predicted the F_S using Markov chain Monte Carlo (MCMC) technique. They tested twenty different configurations and among those the best MSE and R^2 were 0.0147 and 0.823 in the training phase and 0.0231 and 0.766 in the testing phase. Therefore, the proposed model achieved a satisfying level of accuracy for this purpose. Zhou *et al.* (2019) employed gradient boosting machine (GBM) for predicting the stability of real-world slopes.

With reference to area under the curve (AUC) of 0.900, as well as the Cohen's kappa of 0.7324, the GBM was found to be a robust learner for the mentioned application. Sari *et al.* (2019a) determined the slope F_S using support vector regression (SVR). Kang *et al.* (2017) implemented Gaussian process (GP) technique with sixteen covariance functions to predict the F_S. By comparing with tools like ANN and support vector machine (SVM), it was found that the proposed model gives better or equal results, and therefore, it can be an effective predictive model.

Adaptive neuro-fuzzy inference system (ANFIS) (Jang 1993) is a powerful member of the machine learning family applied to various non-linear simulations. Sari *et al.* (2019b) used this model for predicting the F_S of biotechnical slopes. Fattahi (2017) investigated the suitability of the ANFIS implemented with three clustering methods including grid partitioning (GP), fuzzy c-means clustering method (FCM), and subtractive clustering method (SCM). The results pointed out the higher ability of the SCM. Utilizing remotely sensed data, Mehrabi *et al.* (2020) applied the ANFIS for the analysis of landslide susceptibility. They concluded that it can capture an accurate understanding of this parameter.

Regarding various difficulties in using conventional evaluative methods (e.g., the high dimension of the problem and the local minima issue), metaheuristic approaches have been used by many experts (Nguyen *et al.* 2019, Zhao *et al.* 2020b, Mehrabi and Moayedi 2021). These algorithms are capable of searching a space to attain the optimal solution for the problem in hand (Zhao *et al.* 2020c; Zhao *et al.* 2021b). For instance, Zhao and Foong (2022) studied how the ambient temperature, exhausted vacuum, atmospheric pressure, and relative humidity influence the electrical power output of combined cycle power plants. To achieve the goal, they designed an improved multilayer perceptron by introducing a novel metaheuristic optimizer (i.e., electrostatic discharge algorithm). Compared with conventional methods, metaheuristic optimization performs much better in multiple aspects.

In geotechnical domains, Singh and Banka (2020), Himanshu *et al.* (2020), and Mishra *et al.* (2020a) used these techniques for locating critical failure surfaces. Multiverse optimisation (MVO) and ant colony optimization (ACO) are capable metaheuristic techniques that were used by Mishra *et al.* (2020b) and Mayank *et al.* (2020) for this purpose. Different optimizers have also been popular for other objectives like landslide susceptibility analysis (Moayedi *et al.* 2019a, Moayedi *et al.* 2019b) settlement prediction (Moayedi *et al.* 2019c; Zhang *et al.* 2020a), and shear strength modeling (Gao *et al.* 2020, Foong *et al.* 2020). Lin *et al.* (2018) showed the excellence of gravitational search algorithm (GSA) in comparison with regular machine learners such as random forest and SVM. Lohar *et al.* (2021) used optimization algorithms like particle swarm optimization (PSO) to achieve an optimal analysis of slope stability parameters.

Ye *et al.* (2020b) optimized the performance of an ANN using four metaheuristic algorithms, namely spotted hyena optimizer (SHO), league champion optimization algorithm (LCA), shuffled frog leaping algorithm (SFLA), and salp swarm algorithm (SSA). A comparison between the accuracies revealed the superiority of the SSA-based model with a correlation of 0.9937. Likewise, Moayedi *et al.* (2019d) could improve the accuracy of the ANN in predicting the F_S. In this way, they employed Harris hawks optimization (HHO) which reduced root mean square error (RMSE) of the ANN from 2.0806 to 1.6546. In a research by Luo *et al.* (2019) predicted the F_S of a quarry mine by a combination of cubist algorithm and the PSO. With the RMSE and the coefficient of determination (R^2) of 0.025 and 0.981, respectively, it outperformed benchmark conventional techniques including SVM, classification and regression tree (CART), and kNN. Rukhaiyar *et al.* (2018) combined the ANN with PSO algorithm to obtain an optimal predictive model for the F_S simulation. After optimizing the configuration of both ANN and PSO, their best model achieved the R^2 and RMSE of 0.87 and 0.21. Further applications of such optimizers can be found in Ref.s (Xue 2017, Gao *et al.* 2020) for tuning the processors like ANN and LSSVM.

Referring to the above literature, integrative models have been highly regarded for slope stability assessments. More particularly, hybrid models whole one part is a metaheuristic algorithm could reliably explore the dependency of the slope stability on various geometrical and environmental conditions through supervising the training of the intelligent tools. However, previous studies have mostly focused on models like ANN and SVM as the to-be-optimized model, while ANFIS-metaheuristic tools have shown great promise for similar domains as well (Xie *et al.* 2021a). Therefore, testing optimized ANFIS models may be a potential way toward more efficient slope stability evaluations.

On the other hand, regarding the optimizer component of the hybrid models, earlier works have dealt with former generation of metaheuristic algorithms like genetic algorithm (GA) and particle swarm optimization (PSO) (Yang *et al.* 2020). Hence, the main effort of this paper is filling these gaps of knowledge through evaluating various novel ANFIS-metaheuristic hybrids applied for predicting the F_S of a single-layer cohesive slope which withstands a footing. Eight metaheuristic algorithms, namely equilibrium optimizer (EO), Harris hawks optimization (HHO), water cycle algorithm (WCA), biogeography-based optimization (BBO), dragonfly algorithm (DA), grey wolf optimization (GWO), and teaching learning-based optimization (TLBO) are responsible for adjusting the membership function (MF) parameters of an ANFIS. Moreover, the performance of a typical ANFIS is also considered as a comparative benchmark for hybridized versions.

2. Methodology and data

2.1 Data and statistics

It is well-established that to predict any parameter, the models have to first obtain a valid perception from its behavior. This analysis reveals the dependence of the desired parameter on the independent factors. Once the behavior is correctly understood, the parameter can be predicted for new conditions that have not been dealt with so far.

In this research, the F_S of a single-layer cohesive slope that bears a footing is the target parameter dependent on four systematic parameters, namely undrained cohesive strength (C_U), slope angle (α), exerted surcharge (on the footing) (S_F), and the ratio of setback distance (R_{SD}). More clearly about the R_{SD}, it is obtained as the distance between the footing and slope crest over the footing dimension.

To achieve the numerical records of these parameters, Optum G2 software (Krabbenhoft *et al.* 2015) was used to model a single-layer cohesive soil slope with a footing on it.

This software can yield the F_S for different geometrical/loading scenarios. In this sense, a total of 630 scenarios were implemented for 7 values of C_U within (25-400 *kPa*), 5 values of α within (15-75°), 3 values of S_F within (50-150 kN/m^2), and six values of R_{SD} within (0-6). However, four parameters of internal friction angle = 0°, Poisson ratio = 0.35°, and soil unit weight = 18° kN/m^3, were fixed throughout the modeling.

For each scenario, the obtained value of the F_S was recorded for the corresponding C_U, α, S_F, and R_{SD}, and eventually, a dataset consisting of 630 rows and 5 columns was created. Fig. 1 shows the variations of the F_S, C_U, α, S_F, and R_{SD}.

Moreover, Table 1 gives the statistical indicators of the input and target parameters. As is denoted, the values of the F_S range from 0.8 to 28.55 where the average value is 6.96. Moreover, based on the regression analysis, the largest correlation with the F_S is obtained for the input C_U (R^2 = 0. 8134). It can also be derived from Figs. 1(a) and 1(e) wherein both parameters have an upward overall trend. In other words, the soil-footing system has been more stable for the soil with larger C_Us.

The existing 630 records were divided into the training dataset with 504 records and the testing dataset with 126 records. In other words, the ratio of 80:20 is used for designating the samples for learning and reproducing the F_S pattern. Remarkably, in order to have representatives from the whole data in both datasets, a random selection was considered for this process.

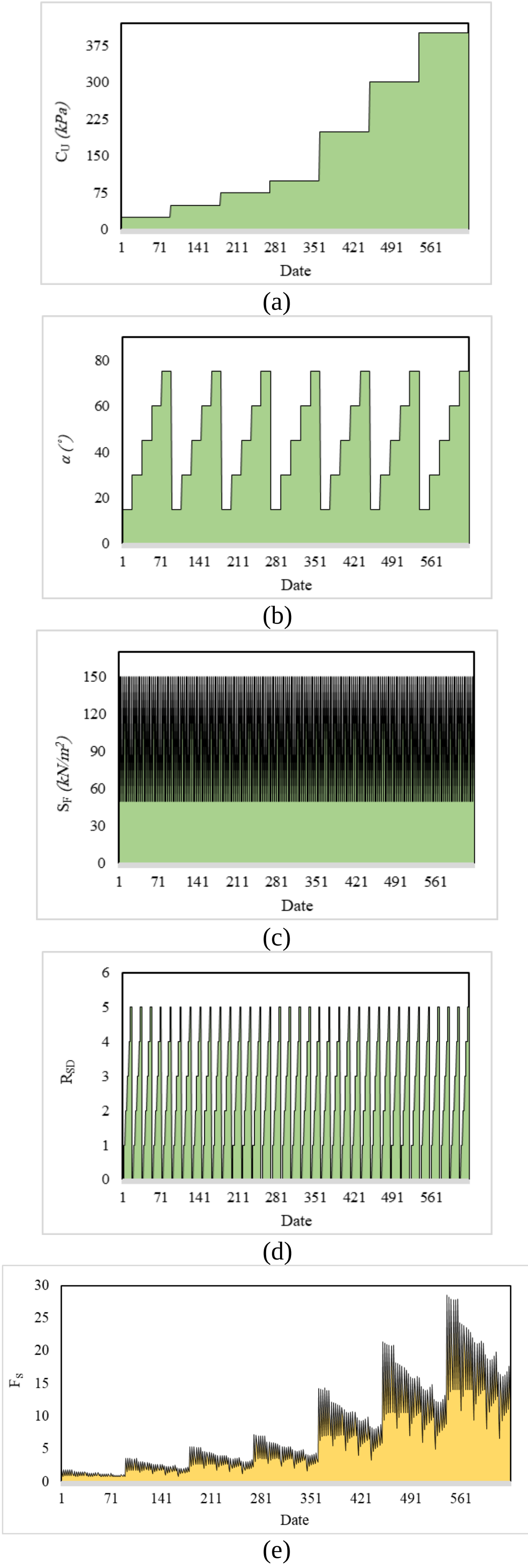


Fig. 1 The variations of the components of the used dataset

2.2 Methodology

Eight metaheuristic algorithms are interactively employed in this study. Due to the long explanations that exist for each model, the mechanism of one algorithm (i.e., the WCA) is mathematically explained as an example, and the remaining ones are addressed in Table 2 to be studied in previous literature.

Table 1 Statistical analysis of the used dataset

Features	Descriptive index						
	Mean	Skewness	Standard Deviation	Sample Variance	Minimum	Maximum	*R*2 with F_S
C_U *(kPa)*	164.29	0.67	130.94	17144.56	25	400	0.8134
α *(°)*	45.00	0.00	21.23	450.72	15	75	0.0333
S_F *(kN/m²)*	100.00	0.00	40.86	1669.32	50	150	0.0698
R_{SD}	2.50	0.00	1.71	2.92	0	5	0.0023
F_S	6.96	1.18	6.10	37.22	0.8	28.55	1.0000

Table 2 A brief explanation of the used algorithms

Algorithm	Developer	Inspiration	Reference
EO	Faramarzi *et al.* (2020)	Equilibrium state of systems	(Sun *et al.* 2022, Zhang and Lin 2022)
HHO	Heidari *et al.* (2019)	Harris hawks' behavior	(Balakrishnan *et al.* 2022, Issa and Samn 2022)
BBO	(Simon 2008)	Biogeography behavior of species	(Ghatte 2021, Kadri and Koudil 2022)
DA	(Mirjalili 2016)	Dragonfly behavior	(Jawad *et al.* 2021, Too and Mirjalili 2021)
GWO	(Mirjalili *et al.* 2014)	Grey wolf behavior	(Issac *et al.* 2022, Wang *et al.* 2022)
TLBO	Rao *et al.* (2011)	Teaching and learning process	(Bhatt 2022, Muther *et al.* 2022)

2.2.1 The WCA

Eskandar *et al.* (2012) introduced the WCA with having the natural water cycle in mind as the inspiration. Raindrops play the role of the initial population where the best one is considered as a sea, worthy ones form the rivers, and the remaining raindrops are selected as streams that run into the rivers and sea. The population is described as

$$NS_j = [X_1, X_2, \ldots, X_{Nvar}] \tag{1}$$

in which $Nvar$ symbolizes the problem dimension.

Concerning the flow strength, Eq. (2) determines the destination of the raindrops (the sea or rivers)

$$NS_n = round\left\{\left|\frac{Cost_n}{\sum_{i=1}^{N_{RS}} Cost_i}\right| \times N_{Raindrops}\right\}, \quad n = 1, 2, \ldots, N_{RS} \tag{2}$$

in which $Cost_n$ is the cost function of the raindrop, N_{RS} stands for the number of rivers plus the single sea. Also, $N_{Raindrops}$ represents the remaining population (raindrops going directly toward the rivers or the sea).

In the WCA, the sea is the final destination of the rivers and streams. Given *r* as a random value with uniform distribution, and *C* as a value between 1 and 2, Eqs. (3) and (4) give the updating procedure of the streams and rivers.

$$New\_X^i_{stream} = X^i_{stream} + r \times C \times (X^i_{river} - X^i_{stream}) \tag{3}$$

$$New\_X^i_{river} = X^i_{river} + r \times C \times (X^i_{sea} - X^i_{river}) \tag{4}$$

After obtaining new positions, the stream and river exchange their position if the stream gives a better-fitted solution. The river and the sea do the same if the river gives a better-fitted solution.

A so-called parameter "d^i_{max}" is defined to encourage (or forbid) extra search near the sea. In this sense, Eq. (5) can be written

$$d^{i+1}_{max} = d^i_{max} - \frac{d^i_{max}}{T} \tag{5}$$

where T denotes the maximum number of iterations.

When the raining process occurs again, new streams are formed. Given γ as the search area near the sea, Eq. (6) is specified to the streams that move directly into the sea.

$$X^{new}_{stream} = X_{sea} + \sqrt{\gamma} \times randn\,(1, X_{Nvar}) \tag{6}$$

where $randn$ is a random value with a normal distribution (Roeva *et al.* 2020).

2.3 Accuracy indicators

Based on Eqs. (7) to (9), mean absolute error (MAE), the RMSE, and mean absolute percentage error (MAPE) are used for measuring different types of error between the predicted and expected F_Ss (i.e., $S_{i_{prediction}}$ and $S_{i_{expected}}$ in the formulations). Moreover, the agreement between these values is reported by Pearson correlation coefficient (R_P). This index is formulated in Eq. (10).

$$MAE = \frac{1}{K}\sum_{i=1}^{K} |S_{i_{expected}} - S_{i_{prediction}}| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K} [(S_{i_{expected}} - S_{i_{prediction}})]^2} \tag{8}$$

$$MAPE = \frac{1}{K}\sum_{i=1}^{K} \left|\frac{S_{i_{expected}} - S_{i_{prediction}}}{S_{i_{expected}}}\right| \times 100 \tag{9}$$

$$R_P = \frac{\sum_{i=1}^{K}(S_{i_{prediction}} - \bar{S}_{prediction})(S_{i_{expected}} - \bar{S}_{expected})}{\sqrt{\sum_{i=1}^{K}(S_{i_{prediction}} - \bar{S}_{prediction})^2}\sqrt{\sum_{i=1}^{K}(S_{i_{expected}} - \bar{S}_{expected})^2}} \tag{10}$$

In the above equations, K stands for the number of evaluated FS pairs.

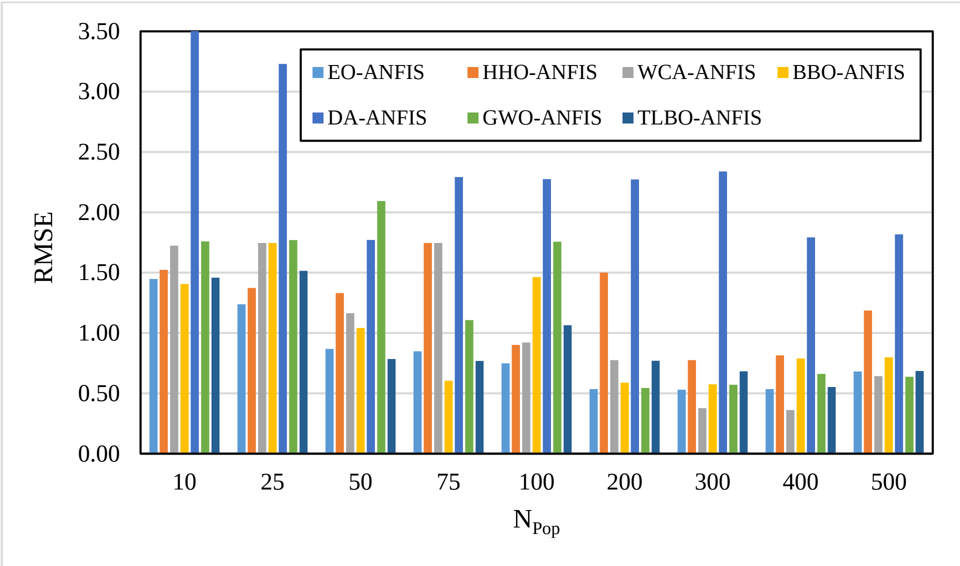


Fig. 2 RMSE results of the performed sensitivity analysis

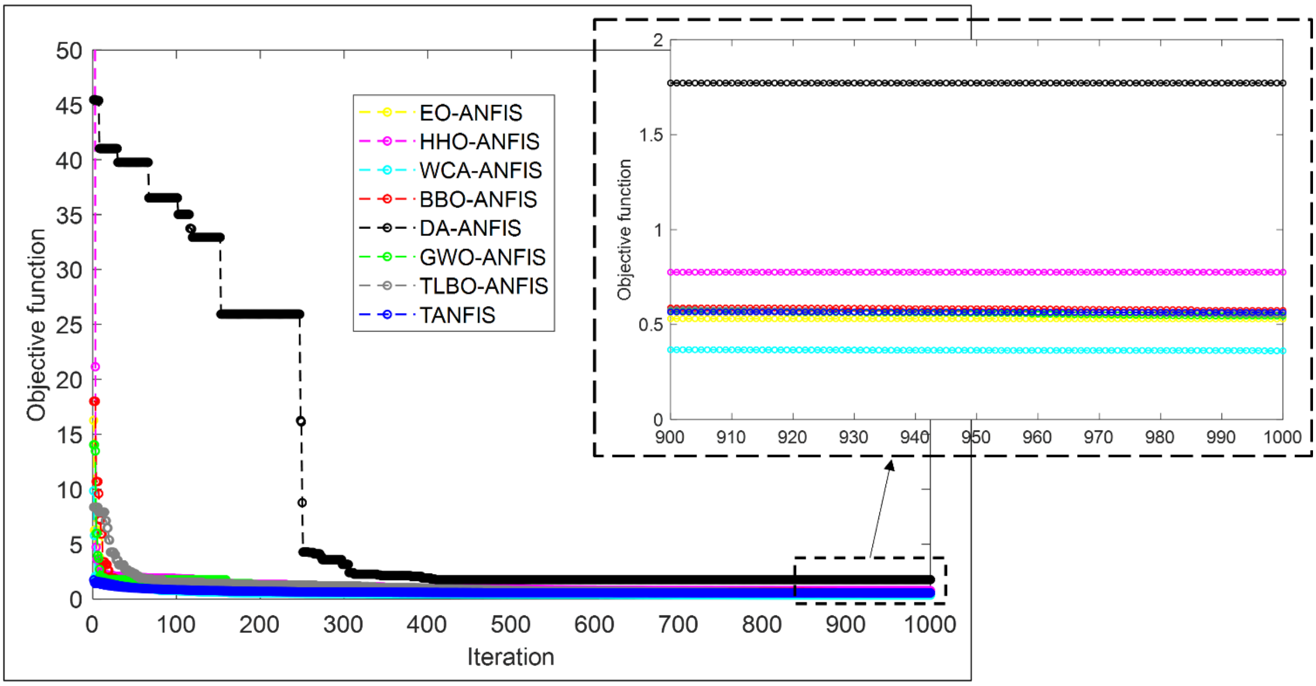


Fig. 3 The convergence proceeding of the used models

3. Results and discussion

3.1 Training and parameter adjustment

It was explained that when an ANFIS is trained, the MF parameters are adjusted by the assigned algorithm and based on the designated data (Roy 2007, Moayedi *et al.* 2019a). Note that, the training data are normally used for this process. In this work, seven metaheuristic optimizers of EO, HHO, WCA, BBO, DA, GWO, and TLBO take the responsibility of training the ANFIS. To better understand the adjustment of MFs, the readers may refer to a study by Moayedi *et al.* (2020) in which ANFIS is optimized by the PSO, GA, and differential evolution (DE) algorithms (see Fig. 3 of the cited study).

A typical fuzzy c-means ANFIS (TANFIS) is also used as a benchmark model. The number of cluster in the used ANFIS model was 7 (obtained after testing various values), with 1000 epochs and backpropagation strategy. For optimization, each algorithm tries to tune the ANFIS parameters according to the goodness of the training data. This process takes place within an iterative effort in which the algorithm tries to improve the solution by finding a richer source (a better sea in the WCA). The quality of the solution is evaluated in each iteration using an objective function (here is the RMSE). The improvement process continues until the algorithm reaches the maximum number of iterations.

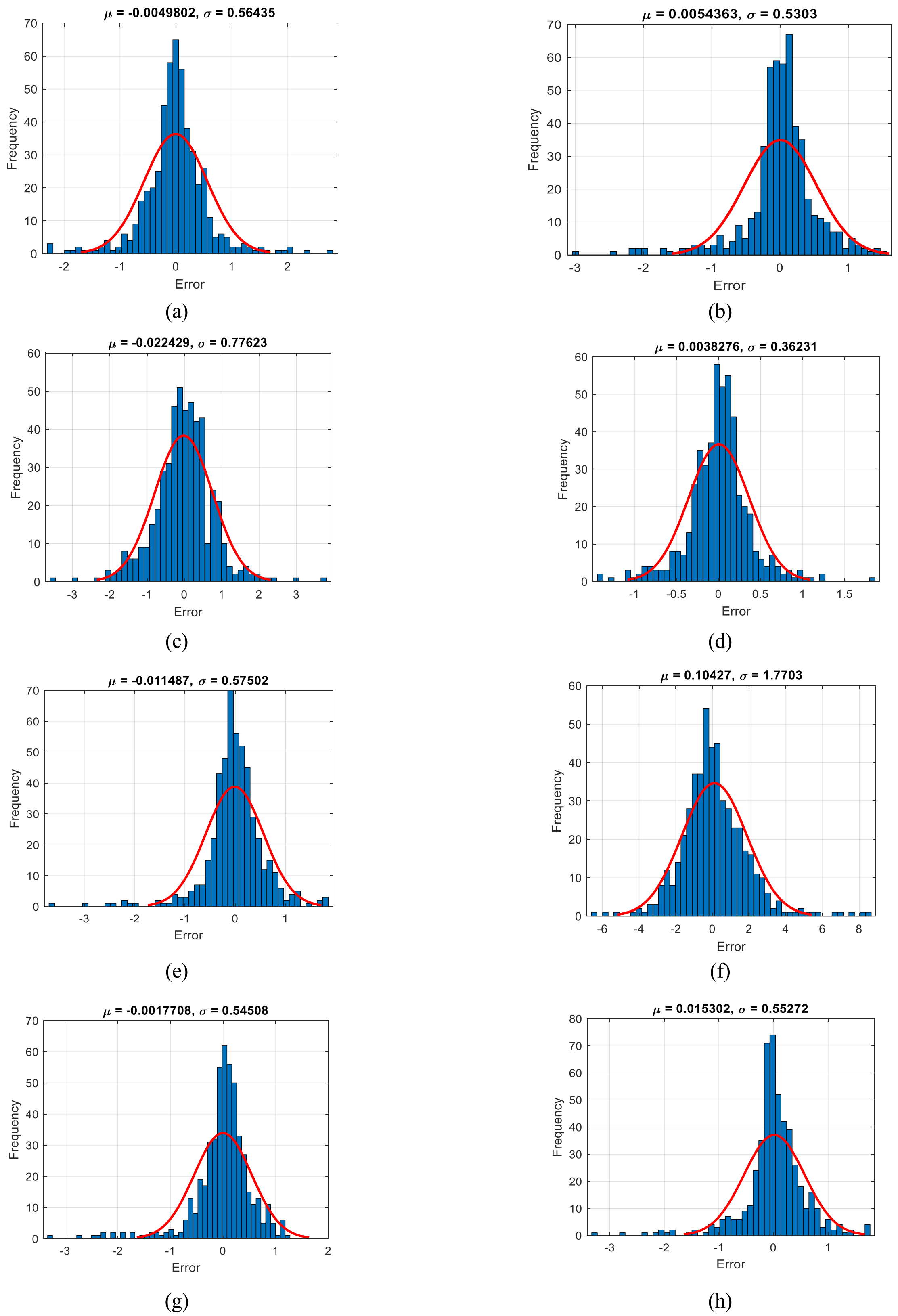


Fig. 4 The correlation of the results for (a) TANFIS, (b) EO-ANFIS, (c) HHO-ANFIS, (d) WCA-ANFIS, (e) BBO-ANFIS, (f) DA-ANFIS, (g) GWO-ANFIS, and (h) TLBO-ANFIS

Due to the undeniable effect of the population size (N_{Pop}) on the performance of metaheuristic algorithms, the best N_{Pop} is identified by this trial and error practice (among nine tested populations with 10, 25, 50, 75, 100, 200, 300, 400, and 500 search agents). As the results in Fig. 2 indicate, it showed that the EO, HHO, WCA, BBO, DA,

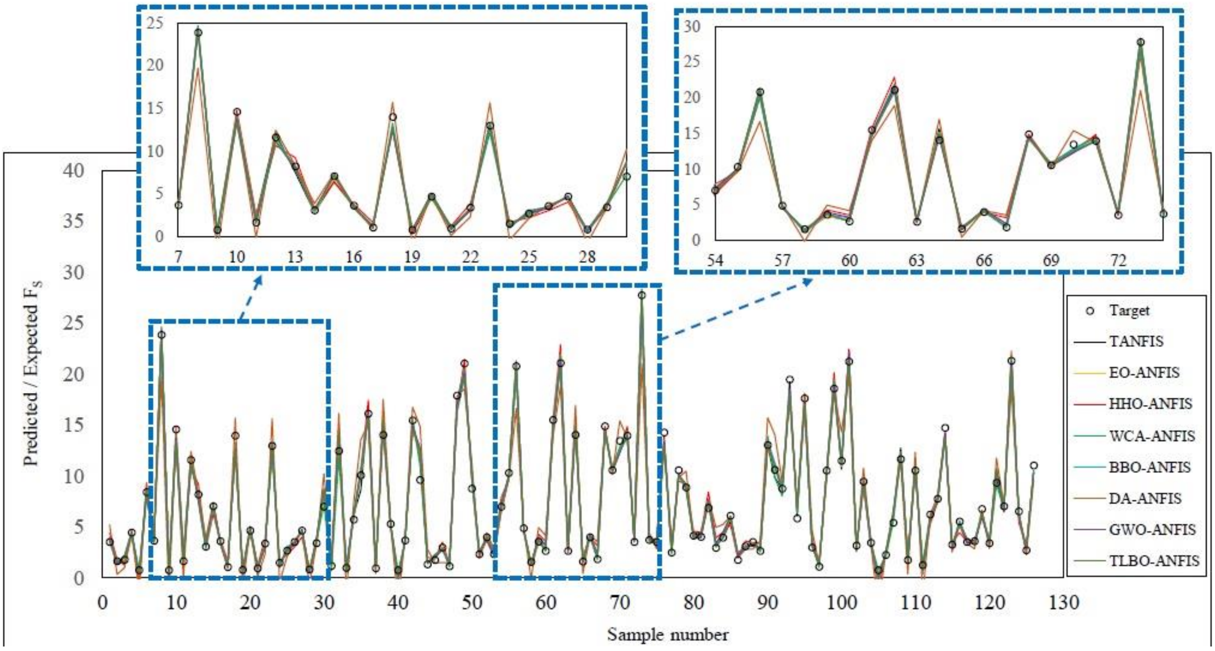


Fig. 5 Comparing the expected and predicted *FSs*

GWO, and TLBO gave the best solution when N_{Pop} = 300, 300, 400, 300, 50, 200, and 400.

Fig. 3 presents the convergence curves of the selected ANFIS networks. In all of them, the models are executed with 1000 iterations to minimize the learning error properly.

The curves of the TANFIS, EO-ANFIS, HHO-ANFIS, WCA-ANFIS, BBO-ANFIS, DA-ANFIS, GWO-ANFIS, and TLBO-ANFIS ended up with the RMSEs of 0.5638, 0.5298, 0.7757, 0.3619, 0.5745, 1.7716, 0.5445, and 0.5524, respectively. These values indicate that the models have captured the F_S behavior with satisfactorily good reliability. It can also be deduced from the MAEs of 0.3763, 0.3424, 0.5659, 0.2529, 0.3796, 1.2769, 0.3548, and 0.3619, as well as the MAPEs of 8.8038, 7.4872, 17.9271, 5.4868, 10.5278, 42.5939, 8.6321, and 9.2434%. Furthermore, the R_Ps obtained as 0.9957, 0.9962, 0.9919, 0.9982, 0.9955, 0.9575, 0.9960, and 0.9959 which reflects high agreement between the expected and predicted F_Ss. Fig. 4 shows the training results (i.e., the histogram of the simple error obtained for each F_S pair).

3.2 Prediction quality assessment

As explained, the models treat the testing dataset (i.e., 126 records) as stranger problem conditions. If they can predict the F_S accurately in this phase, it means that the MF parameters tuned by the proposed algorithms have established a reliable fuzzy relationship between the F_S and C_U, α, S_F, and R_{SD}.

Similar to the training phase, the models gave an excellent prediction in this phase. Fig. 5 shows the expected F_Ss and the patterns produced by the ANFIS-based mdoels. In a glance, almost all models could properly follow the F_S behavior. For example, the largest F_S was 27.7800 (obtained for the soil-footing system with C_U = 400 *kPa*, $\alpha = 15^{\circ}$, S_F = 50.0 kN/m^2, and R_{SD} = 4) that is predicted to be 26.7018, 28.2853, 25.9792, 26.6349, 28.3494, 21.0145, 27.9693, and 28.2916 by the TANFIS, EO-ANFIS, HHO-ANFIS, WCA-ANFIS, BBO-ANFIS, DA-ANFIS, GWO-ANFIS, and TLBO-ANFIS, respectively. Two magnified sections present a more detailed illustration from the comparison between the target and outputs.

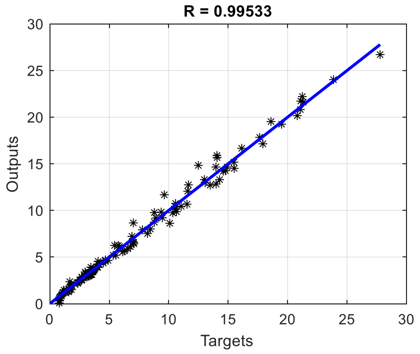
The obtained RMSEs were 0.5896, 0.5850, 0.7959, 0.4312, 0.6364, 1.7199, 0.5732, and 0.6073 that along with the MAEs of 0.4118, 0.3842, 0.6195, 0.3004, 0.4368, 1.2329, 0.3978, and 0.4048 indicate an accurate estimation for all models. Besides the MAPEs were 8.8372, 8.5334, 18.0008, 5.2123, 12.0921, 39.4956, 9.7099, and 9.8298% reflect a similar performance.

Moreover, Fig. 6 gives the regression charts of the testing phase. In these charts, each point has the coordinate $\begin{bmatrix} x \\ y \end{bmatrix}$ so that x = expected F_S and y = predicted F_S. Thus, the ideal prediction occurs when all points are on the line $y = x$. The R_{PS} were 0.9953, 0.9953, 0.9913, and 0.9974, 0.9944, 0.9600, 0.9955, and 0.9949 indicating a high level of correlation for all used models.

3.3 Comparison

While all models could promisingly understand and reproduce the F_S behavior, there are some distinctions between their capability. In this section, these distinctions are focused on time and accuracy to introduce the most efficient fuzzy predictive tool.

All accuracy indices (as summarized in Table 3) pointed out the superiority of the WCA-ANFIS in the training phase. After that, the EO-ANFIS, GWO-ANFIS, TLBO-ANFIS, TANFIS, BBO-ANFIS, HHO-ANFIS and DA-ANFIS gained the next positions. It means that employing



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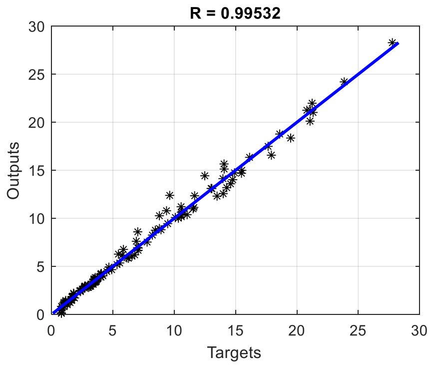

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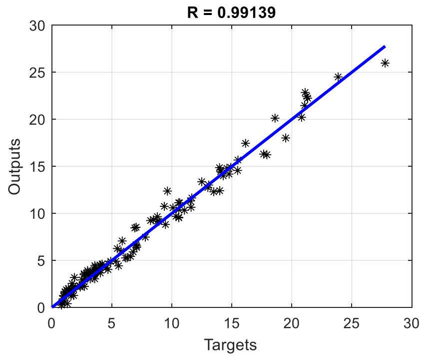

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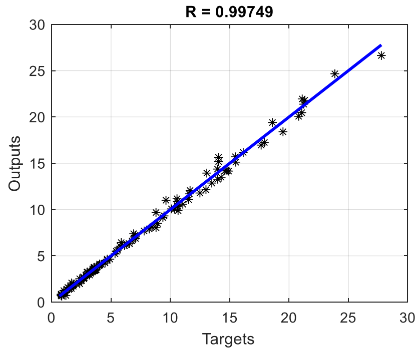

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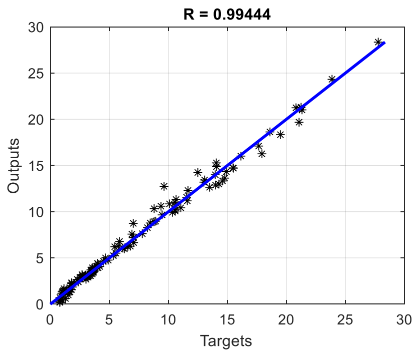

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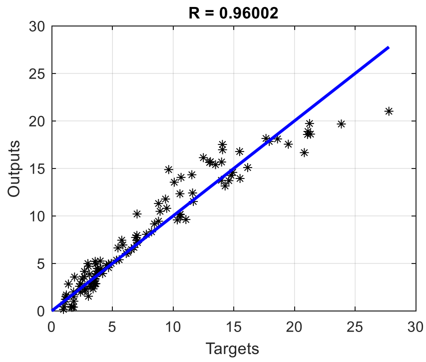

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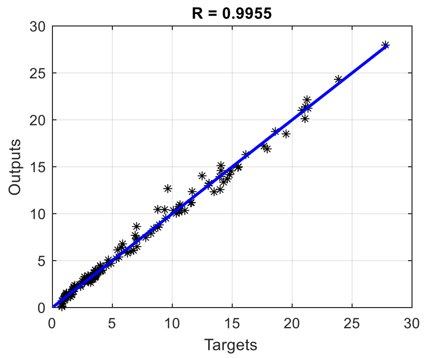

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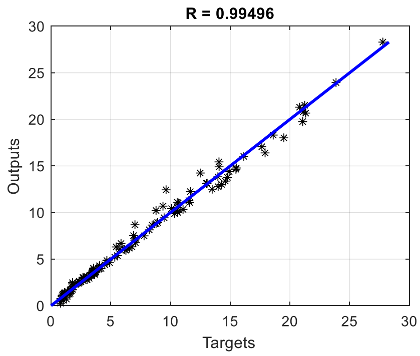

(h)

Fig. 6 The correlation of the results for (a) TANFIS, (b) EO-ANFIS, (c) HHO-ANFIS, (d) WCA-ANFIS, (e) BBO-ANFIS, (f) DA-ANFIS, (g) GWO-ANFIS, and (h) TLBO-ANFIS

the WCA, EO, GWO, and TLBO metaheuristic techniques has resulted in a higher quality training of the AFNIS, compared to the typical methods. For example, the decline of the RMSE from 0.5638 to 0.3619, 0.5298, 0.5445,

Table 3 Summarized accuracy results of the used models

Models	Accuracy indicator							
	Training				Testing			
	MAE	RMSE	R_p	MAPE	MAE	RMSE	R_p	MAPE
TANFIS	0.3763	0.5638	0.9957	8.8038	0.4118	0.5896	0.9953	8.8372
EO-ANFIS	0.3424	0.5298	0.9962	7.4872	0.3842	0.5850	0.9953	8.5334
HHO-ANFIS	0.5659	0.7757	0.9919	17.9271	0.6195	0.7959	0.9913	18.0008
WCA-ANFIS	0.2529	0.3619	0.9982	5.4868	0.3004	0.4312	0.9974	5.2123
BBO-ANFIS	0.3796	0.5745	0.9955	10.5278	0.4368	0.6364	0.9944	12.0921
DA-ANFIS	1.2769	1.7716	0.9575	42.5939	1.2329	1.7199	0.9600	39.4956
GWO-ANFIS	0.3548	0.5445	0.9960	8.6321	0.3978	0.5732	0.9955	9.7099
TLBO-ANFIS	0.3619	0.5524	0.9959	9.2434	0.4048	0.6073	0.9949	9.8298

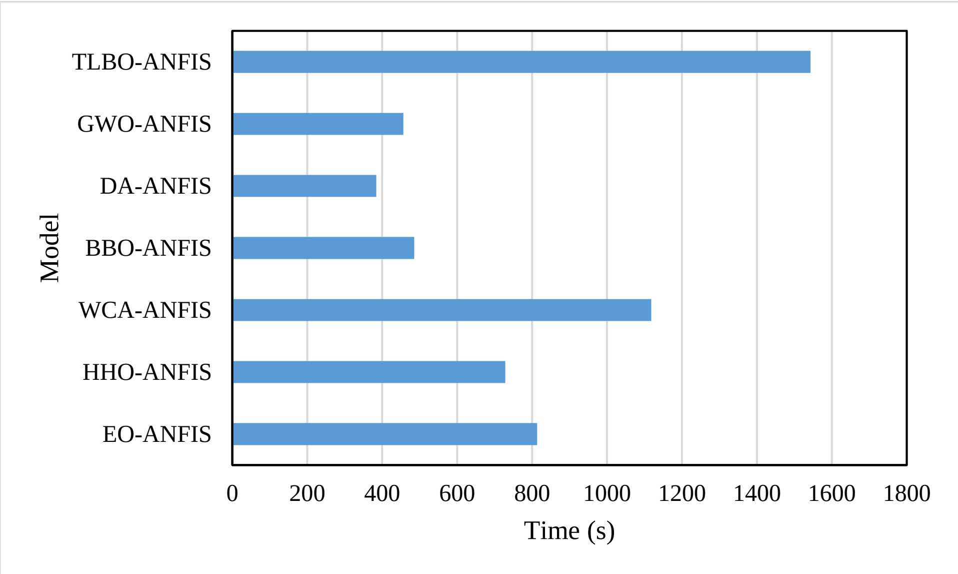

Fig. 7 Optimization time of the used algorithms

0.5524 professes the higher accuracy of the hybrid tools. However, the same index showed that the TANFIS performs more accurately than the BBO-ANFIS, HHO-ANFIS and DA-ANFIS.

The same comparison was executed for the testing data. The results demonstrated the best goodness of fit for the WCA-ANFIS. Following this, the EO-ANFIS and GWO-ANFIS presented a more reliable prediction of the F_S compared to the TANFIS. A close competition was observed between the TANFIS and TLBO-ANFIS, and again, the TANFIS outperformed BBO-ANFIS, HHO-ANFIS, and DA-ANFIS.

Different reasons can justify these distinctions between the optimization robustness of the algorithms. For instance, the goodness of the initial solution (i.e., the first RMSE in Fig. 3) may influence the solution. However, it is worth mentioning that the initial response is stochastic, and the population is scattered within the space. Another reason could be the optimization strategy. In the case of WCA, the superior accuracy could be due to its action in all directions (Sadollah *et al.* 2016).

With this in mind that time is an effective parameter in engineering works, the time-efficiency of the used models is also evaluated. Fig. 7 compares the time of the hybrid models for the selected N_{Pop} (system: Intel Core i7 64-bit with 16 gigs of RAM). According to this figure, the most accurate configurations (N_{Pop} of 300, 300, 400, 300, 50, 200, and 400 for EO, HHO, WCA, BBO, DA, GWO, and TLBO) whose results were discussed above, took around 813.5, 728.7, 1118.1, 485.6, 384.1, 456.5, and 1543.2 seconds for optimizing the ANFIS. It is derived that, TLBO is a slow algorithm. Considering the models which improved the accuracy of TANFIS, the WCA despite the most accurate analysis, takes larger time than the EO and GWO.

Although the implementation of TANFIS was considerably faster (around 6 seconds), this model was not introduced as the most efficient one because in subtle engineering works, accuracy comes above other parameters. Therefore, referring to both accuracy and time assessments, GWO-ANFIS may be a suitable model for time-dependent analysis, while the WCA-ANFIS is recommended for accuracy-dependent works.

3.4 Further discussion and literature assessment

It was observed that the prediction of ANFIS is in a satisfying level of accuracy. Overall, according to many earlier works, conventional models like ANN and ANFIS are suitable for normal problems. But as is known, there are some computational complexities, especially for large datasets, that necessitate assigning the training task of these models to optimization algorithms like EO and WCA. These models sometimes get trapped in local minima area and are not able to find the optimum solution (*Karaboga et al.* 2007). In other words, the solution is fine, but can be better. This point can be better visualized in the correlation diagrams Fig. 6. On the other hand, in subtle engineering works like slope stability, the maximum accuracy is required as a false assessment may lead to a disaster. For instance, overestimating the factor of safety indicates high stability of a slope which gives the permission for pitching an intolerable structure over it. Therefore, when an improvement can occur, it can be very helpful toward more reliable decisions.

During implementing the models, it was observed that a few algorithms like BBO-ANFIS need an initial supervision because, in some cases with small populations, the training error was not reducing over iterations and the user should have re-implemented the algorithm to tackle this problem. However, it can be simply solved by considering a condition in coding the model. Also, while in this study the original data was used for comparison purpose, a data preprocessing may be of interest for reducing the complexity of the analysis. Like the importance assessment carried out by Ye *et al.* (2020b), considering the most important factors may result in the betterment of analyzing the correspondence between the F_S and slope characteristics. Trying similar metaheuristic algorithms with other benchmarks like SVR is another appreciable idea for future works.

Compared to previous works that have used this dataset for developing intelligent hybrid models, the models of this study achieved notable improvements. For instance, Foong and Moayedi (2021) used the EO and vortex search algorithm (VSA) coupled with an ANN. Having the WCA-ANFIS as the representative of this study, this model achieved a training RMSE of 0.3619, while this value for the EO-MLPNN and VSA-MLPNN was 0.3891 and 0.4383. Also, in the testing phase, WCA-ANFIS outperformed VSA-MLPNN (prediction errors of 0.4129 vs. 0.5155). In another effort by Ye *et al*. (2020b), the SSA-MLPNN and LCA-MLP were outstanding models that achieved the RMSE of 0.4463 and 0.6704 for training and 0.4825 and 0.7648 for testing phase. It is indicated that the WCA-ANFIS results are comparably more accurate than these models, and more considerably than two other used models (i.e., SHO-MLP and SFLA-MLP). Also, the GWO-ANFIS of this study presented a more reliable prediction (RMSEs = 0.5445 and 0.5732) than LCA-MLP, SHO-MLP, and SFLA-MLP.

These two studies were selected for comparison because they have used the same dataset for their prediction.
Hence, another idea for future works can be testing the generalizability of all discussed models (including ANN and ANFIS-based hybrids) by applying them to more than one dataset. Assessing such results gives a comprehensive comparison from the potential of various models.

Altogether, the findings of this study yielded applicable results regarding the indirect early prediction of slope stability. First, the feasibility of the conventional ANFIS model was tested and proved for this purpose. Second, a potent comparison among the new generation of metaheuristic algorithms was performed and some could even enhance the conventional ANFIS and provide more accurate estimations. Third, ANFIS-metaheuristic models can provide efficient (in terms of both accuracy and time of computation) for predicting factor of safety. Fourth, outstanding models were superior to some previously used hybrids which are the combination of ANN and metaheuristic algorithms.

4. Conclusions

Intelligent models have effectively assisted engineers in predicting the stability situation of different slopes. This study was conducted to improve the accuracy of a leading predictive model applied to the mentioned problem. An ANFIS was trained by various metaheuristic strategies for predicting the F_S of a cohesive soil slope. By comparing the accuracy of the created hybrids with a typical ANFIS, valuable improvements were found in both analyzing and generalizing phases. The fuzzy networks developed by the EO, GWO, and WCA were superior to TANFIS. However, the use of TANFIS is preferred over other hybrids including the DA-ANFIS and HHO-ANFIS. While the WCA provided the best-fitted solution to the problem, examining the optimization speed revealed the fastest solution for the GWO. Moreover, these models were more powerful than metaheuristic algorithms similarly applied to ANN in previous studies. To sum up, the findings of this paper can be regarded for real-world applications of intelligent models for approximating the stability of soil slopes.

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