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Prediction the compaction properties of lateritic soils by hybrid ANFIS methods

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Highlights

- Development of new ANFIS-based prediction models to evaluate compaction parameters of lateritic soils
- Performance comparison of imperialist competitive algorithm and whale optimization algorithm by developing two hybrid models
- Both models have a reasonable performance in predicting with R^2 larger than 0.9038 and 0.9692 for the training data
- The ANFIS-WOA has better performance than the ANFIS-ICA model in both training and testing data
- In the training dataset, the values of R^2 and RMSE are 0.9692 and 0.6188 for the ANFIS-WOA model

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Abstract

Empirically, soil compaction is an important aspect in the selection of materials for earth constructions. Due to time constraints and attention to completion resources, it is necessary to develop models to forecast compaction parameters (maximum dry unit weight (γ_{dmax}) and optimum moisture content (ω_{opt}) from easily measured index properties. The main purpose of this study is to scrutinize the applicability of using the hybrid adaptive neuro-fuzzy inference system ($ANFIS$) models for predicting the γ_{dmax} and ω_{opt} related to the standard proctor compaction test of lateritic soils. Results present that both models have a reasonable performance in predicting the γ_{dmax} and ω_{opt} with R^2 larger than 0.9038 and 0.9692 for the training data, representing the acceptable correlation between measured and forecasted γ_{dmax} and ω_{opt}. Regarding developed models, the $ANFIS$ model optimized with whale optimization algorithm (WOA) has the best performance than imperialist competitive algorithm (ICA) model in both training and testing phases for predicting γ_{dmax} and ω_{opt}.

1. Introduction

The continuous depletion of valuable land resources along with structural expansion has been more important in the search for sustainability, so the importance of soil compaction cannot be overemphasized. The world's population is growing from time to time, and there is a constant need for additional infrastructure such as airport runways, roads, buildings, piers, dams, railways, and the like [1]– [3]. Every one of these structures is constructed on soils that, between times, do not have enough tolerating valence to oppose the burdens that are coming on them [4]. In Nigeria, the usual soils utilized for construction that are laterite are some moments realized inappropriate in its normal case for the planned application. So, there is the soil betterment's requirement that compression is between the cheapest and the commonest [5].

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Lateritic is recognized as extensively modified and aerated soils that are organized by in situ weathering and decomposition of parent rocks under subtropical and tropical climatic conditions [6]. Increasing use of this soil is related to its ease of access, compatibility, density, and cheapness. Compression of lateritic soils, similar to various soils, increases soil bearing capacity. It also declines the adverse adaptation value of structures built on such soils and raises the stability of slopes [7]. The strength of foundations is largely based on compression control, which is based on the discovery of the maximum dry weight (γ_{dmax}) of the optimum moisture content (ω_{opt}) in the energy given to the compaction.

Experimental compaction is commonly performed in Nigeria with British Standard Light, West African standard, and British heavy standard. The above-mentioned methods are time and material-consuming, and also laborious [8]. The deficiencies schemed upper with each other with proof by different authors such as Ring et al. [9], Ramiah et al. [10], Blotz et al. [11] and lately Anjita et al. [12], that soil type, particle size figure, and index properties affect the ω_{opt} and γ_{dmax} of soils, tend scholars to suggest connections among $\omega_{opt}/\gamma_{dmax}$ and index characteristics of soils. Index properties such as plastic limit, plasticity index, fine content, liquid limit and many similar cases have been applied former.

Different papers have reported the successful application of ANN-based techniques in civil engineering [13]–[15] or other fileds [16]–[18]. The links suggested were occasionally based upon calculational methods such as regression analysis [11], [19]–[21]. In addition to the fact that several factors are influenced on compaction parameters by Ardakani and Kordanij [22], roughly all experimental links suggested from statistical methods such as regression analysis might have various deviations. However, this idea does not seem to be a good reason. Ardakani and Kordanij [22] used the genetic algorithm along with ANN to extend similar links for estimating ω_{opt} and γ_{dmax}. Chenari et al. [23] employed an evolutionary polynomial regression method for extending the models to estimate ω_{opt} and γ_{dmax}, while Gansoner et al. [24] recently proposed a estimation algorithm to forecast γ_d from penetrometer tests in the calibration chamber.

Artificial neural network predicted γ_{dmax} and ω_{opt} considered a soil stabilizing compound. Multilayer perceptron neural network (MLP) was used for accurate modeling of improved soil γ_{dmax} and ω_{opt}. Modified ANN was developed for estimating explicit formulas for γ_{dmax} and ω_{opt}. The results showed that the accuracy of the models was admissible in comparison with the experimental measurements [25]. Linear log regression methods were proposed to estimate γ_{dmax} and ω_{opt} of fine-grained soil, where the model gained through multiple regression could be used for estimating both parameters. Considering γ_{dmax} and ω_{opt}, specific gravity, liquid limit, compaction energy, and grain size are contained in the most suitable model [26]. Another article was conducted to propose empirical relations between γ_{dmax} and ω_{opt} with logarithm of compaction energy and sand content ratio for some lateritic soils. Common errors are in the range of permissible changes and the standards γ_{dmax} and ω_{opt}, so the models are quite strong [27].

The main purpose of this study is to scrutinize the applicability of using the hybrid ANFIS models for predicting the maximum dry unit weight (γ_{dmax}) and optimum water content (ω_{opt}) related to standard proctor compaction test of lateritic soils. For the prediction processes, two hybrid ANFIS models were developed, in which two determination variables of the ANFIS method were specified using different optimization algorithms, named imperialist competitive algorithm (ICA) and whale optimization algorithm (WOA). For the prediction process, six different variables that can affect the values of the γ_{dmax} and ω_{opt} were considered as inputs, named percent of fines (FC), gravel content (G), sand content (S), liquid limit (ω_l), plastic limit (ω_p), and plasticity index (I_p). The novelty is that considered hybrid ANFIS methods have not been proposed to predict the γ_{dmax} and ω_{opt} of lateritic soils.

2. Methodology

2.1. Description of the Dataset

Ghana contains a large diversity of metamorphic rock and Precambrian igneous that could be seen in about half of the country's zone (Fig. 1). The main ingredients are quartzites, granite-gneiss, migmatites, schists, phyllites, and gneiss. The other country's area is underlain by Paleozoic strengthened alluvial rocks referential to the Voltaian organization, including generally sandstones, mudstone, shale, sandy and pebbly beds, and limestones [28].

The observed soil is lateritic soil which can be found in various locations of Africa as residual soils. This soil could be observed in subtropical and tropical countries under specific weather circumstances. Lateritic soils can be utilized in the roads' construction, earth dams, and many other projects. There have been many observations on lateritic soils, and one of the great substantial features is its color, red. Several factors affect the engineering properties and scope efficiencies, such as soil genetic type, degree of weathering and soil texture, soil formation factor, sample depth, and types of dominant clay minerals. The construction area is in the Tarkwaian area. This area was limited to different sections and was planned for simple reference. Figure 2 shows the regional layout for the Tailings Storage Facility (TSF) dam. It also offers about 17 main planned areas. These areas were divided into smaller areas based on the main coordinates.

Specimens of the fresh soil were sampled from deepness of roughly 30cm to 200cm at the time of the construction of Tailnings Storage Facility, TSF dam for gold mine in Tarkwa, Ghana. Totally, different fresh specimens were collected and were analyzed with particle size analysis [29], Atterberg limit tests [30], and standard proctor tests compaction tests [31]. Standard proctor tests were managed manually on the samples. This was utilized to specify the γ_{dmax} and ω_{opt}. The soil's compression was finished utilizing the mechanical energy gained from a striking hammer.

In order to design the prediction process of γ_{dmax} and ω_{opt} related to the standard proctor compaction test of lateritic soils, a dataset was gathered from previously mentioned sites [32]. For the modeling outline, six various parameters effective on the values of γ_{dmax} and ω_{opt}, were selected as input variables, namely percent of fines (FC) (the percent passing through the No. 200 US Sieve), gravel content (G), sand content (S), liquid limit (ω_l), plastic limit (ω_p), and plasticity index (I_p). Selecting these parameters as input variables was according to literature [32] and the comparison purposes was followed. Based on the successful report of literature about dividing percentage of data [33], the collected dataset was divided into two parts, (a) for training the models with the proportion of 3/4 (75% (66 data row)), and (b) for training the models with the proportion of 1/4 (25% (22 data row)). The given Table 1 represent the statistics of variables utilized in models' development.

The correlation between two variables could be computed using the Pearson correlation coefficient (PCC) [34]. The PCC matrix between parameters is visualized for ω_{opt} and γ_{dmax} as presented in Fig. 3. A high positive or negative correlation value could result in difficulties in interpreting the effects of the explanatory variables on the outputs. Considering the results of ω_{opt}, Fig. 3a shows a large number of the CC between any two variables are somewhat small (i.e., lower than 0.486), determining that these variables might not cause multicollinearity problems [35]. Also, the largest negative and positive CC is between ω_{opt} and I_p, and between I_p and ω_l at -0.801 and 0.788, respectively. Regarding γ_{dmax} (see Fig. 3b), the biggest negative and positive CC is between FC and S, and between γ_{dmax} and I_p at -0.77 and 0.834, respectively.

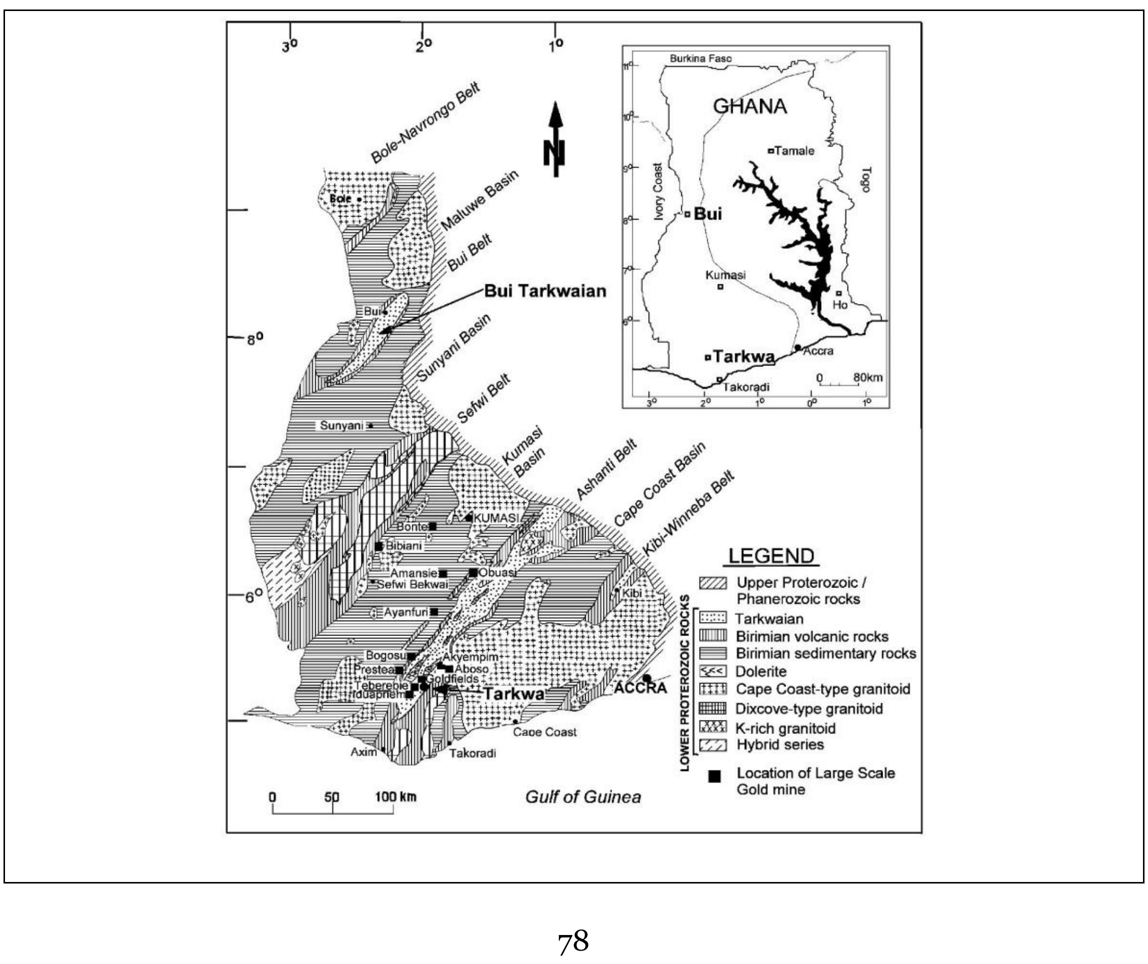


Fig. **1.** Simplified geological map of southwest Ghana [36]

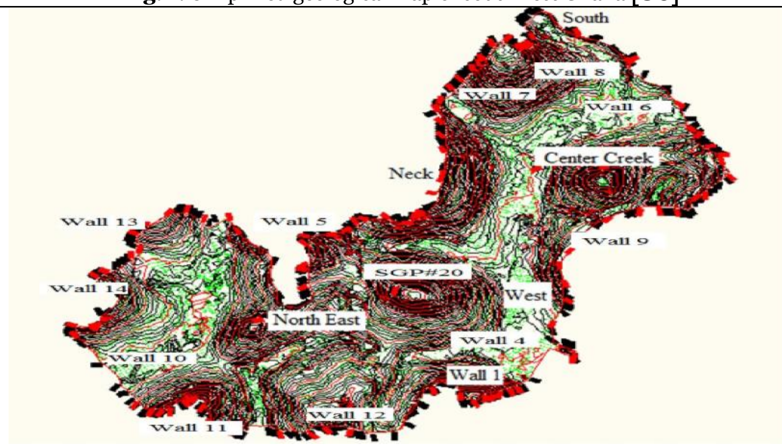
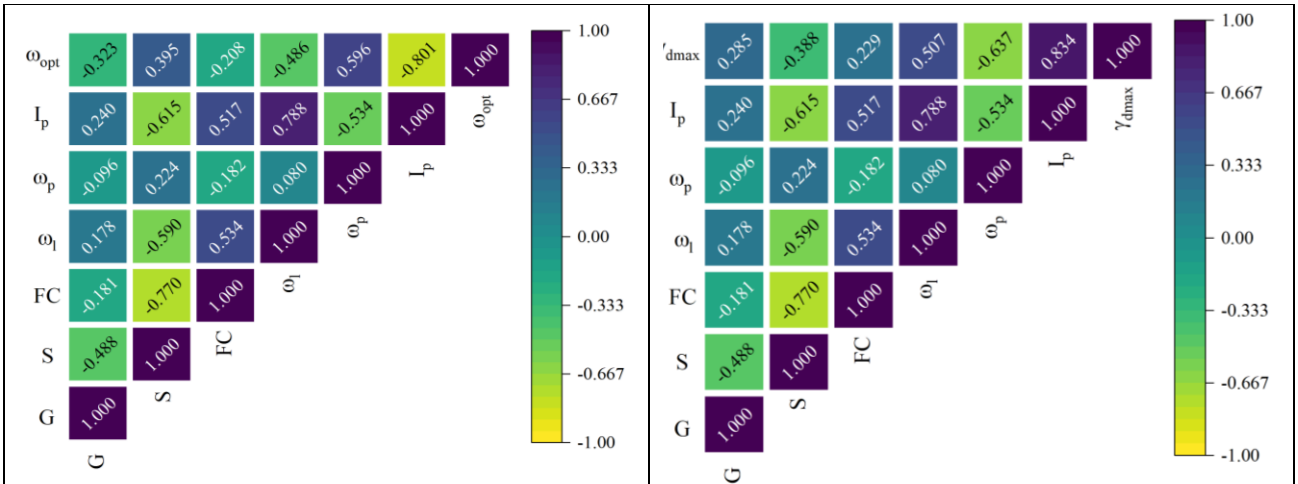


Fig. 2. Site layout of the TSF dam, Tarkwa [32]

Table 1. The statistical indices of the input and output variables

Index	Inputs						Outputs	
	G	S	FC	ω_l	ω_p	I_p	ω_{opt}	γ_{dmax}
Training data								
Minimum	0.7	11.0	8.1	19.6	10.8	0.7	11.3	16.1
Maximum	52.0	76.3	83.4	56.9	32.6	32.9	21.4	24.3
St. deviation	11.832	17.2879	15.815	8.034	4.973	9.253	2.85	1.7013
Average	25.7	36.2	38.1	38.1	18.4	19.5	15.5	19.7
Median	24.0	27.7	37.2	38.3	16.9	22.9	15.6	20.2
Skewness	0.401	0.4934	0.269	-0.121	0.9674	-0.6	0.301	-0.2035
Kurtosis	-0.577	-1.0867	-0.3904	-0.581	0.3827	-0.91	-0.9054	-0.357
Testing data								
Minimum	8.5	12.8	15.3	24.3	9.5	0.9	8.8	16.3
Maximum	44.2	65.3	61.3	51.4	29.1	32.1	24.5	21.5
St. deviation	9.137	17.3677	13.852	7.89	5.45	8.91	3.524	1.3422
Average	24.2	37.2	38.5	38.5	18.2	20.4	15.2	19.6
Median	23.4	34.8	37.8	40.5	18.5	23.5	14.5	19.9
Skewness	0.571	0.1866	0.0282	-0.2	0.23	-0.9	0.57	-0.655
Kurtosis	0.1631	-1.374	-0.9178	-1.1	-0.9	0.17	-0.3975	0.0719



(a) (b)

Fig. 3. PCC between the variables for: a) ω_{opt}, b) γ_{dmax}

2.2. *Applied prediction methods*

2.2.1. *Imperialist competitive algorithm (ICA)*

The imperialist competitive algorithm (ICA) was gained by simulating human social evolution in order to solve optimization problems [37]. It is recognized as one of the evolutionary methods that might decode the continuous function with great efficiency [38]– [40]. In fact, this algorithm is a global search method proposed on the basis of imperialist competition and social policy [41]. Thus, the strongest empire could conquer various colonies with its own resources. Other realms can compete for territory when an empire falls. The main procedure of this algorithm can be explained below steps.

a) Randomly produce primitive empires and search spaces
b) Colonization: The location of the colonies varies according to the position of the countries
c) Random changes happen in the characteristics of each country as a revolution.
d) Swap territory with empire. A colony with a most appropriate location could rise up and control the empire and replace the former empire
e) Empires challenge to conquer the colonies of others
f) Weaker empires would be defeated and deleted. All colonies of weaker empires would be lost. At this stage, the laws of natural selection apply.
g) Check the stop criteria. If the stop criteria are met, stop the competition process. Otherwise, return to the colony assimilation stage (stage b)
h) End.

The given Fig. 4 presents the pseudo-code of the ICA algorithm.

Algorithm: The pseudo code of the imperialist competitive algorithm

```
Initialize population
Do empires formation
While the stopping criterion is not met, do
    For i=1 to Nimp, do
        Mutate the imperialist
        Assimilate cololies by mutated imperialist
    Endfor
    Update the imperialist
    Do imperialist competition strategy
    For i=1 to Nimp, do
        Do imperialist development plans mechanism
    Endfor
    Replace similar colonies with a new producing by initialization procedure
    Apply local search on best imperialist
Endwhile
```

Fig. 4 The ICA's pseudo-code

2.2.2. Whale optimization algorithm

Whale optimization algorithm (WOA) is a congestion technique proposed on the natural remedy of humpback whales [42]–[45]. The WOA method, similar to population algorithms, begins its proficiency with a premier production. After that, it calculates an objective subordinate for each answer of population. In the final step, the optimized solution is selected according to the strategies of whales, surrounding the prey and forming a bubble net. For surrounding, WOA refreshes the most precise answer, hence:

$$\begin{aligned} &SW_i(t+1) = SW_{best}(t) - GD \\ &G = 2cr_2 - c \\ &D = |SW_{best}(t) - SW_i(t)|, E = 2r_1 \end{aligned} \quad (1)$$

D	the space between solution $SW_i(t)$ at iteration (t) and the best respond $SW_{best}(t)$
r_1 and r_2	random coefficients between 1 and 0

where c involves a factor of iteration various in the distance among 2 and 0 and is computed as below:

$$C = c - t\frac{c}{MaxIterw} \quad (2)$$

This algorithm updates the answer with spiral or surrounding techniques as presented in Fig. 5 [44]. At begin point, the surrounding reducing model is carried out with the strategies of factor iteration c (Eq. (2)). Or else, the spiral method is admitted for the target of refresh answers in this technique. WOA creates a helix-shaped movement that is simulated. This motion (Eq. (3)) is practically a particular movement caught by whales close to the best solution (SW_{best}) during preying.

$$SW_i(t+1) = \acute{D}e^{sk}\cos(2\pi k) + SW_{best}(t) \quad (3)$$

$$\acute{D} = |SW_{best}(t) - SW_i(t)| \quad (4)$$

s	The logarithmic spiral shape
k	A random variable between 1 and -1

Also, the WOA answers could be refreshed through transferring between spiral-shaped and decreasing [44], so:

$$SW_i(t+1) = \begin{cases} SW_{best}(t) - GD & if\ r_3 < 0.5 \\ \acute{D}e^{sk}\cos(2\pi k) + SW_{best}(t) & if\ r_3 \geq 0.5 \end{cases} \quad (5)$$

r_3	The possibility of wrapping in that $r_2 \in [1,0]$

Naturally, whales mostly admit other strategies when preying, which describe the random chase technique; In WOA, a random location is picked in the position of the optimized answer; therefore:

$$SW_i(t+1) = SW_r(t) - GD \quad (6)$$

$$D = |E\delta SW_R(T) - SW_i(t)| \quad (7)$$

Fig. 5. Process of the whale Optimization Algorithm

2.2.3. The adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS method has been suggested as a soft calculating method merges fuzzy logic with neural networks [46]. ANFIS was applied chiefly in several engineering studies [47], [48]. This technique is able to simulate and evaluate the mapping links between dependent and independent parameters using a hybrid learning function for specifying the optimal membership function distribution. The base of ANFIS is the if and then rules (Fig. 6). This method contains two phases, a premise part, and a consequent part. Five layers exist within the inference system, each of which consists of several nodes knowns as the node function. Previous layers' nodes emitted output signals. When the node function manipulates the output, it outputs it as an input signal to the sublayer. At the present article, fixed and adaptive nodes are considered to depict which set of variables could be readjusted suitably and to present they could be totally fixed in the system, respectively.

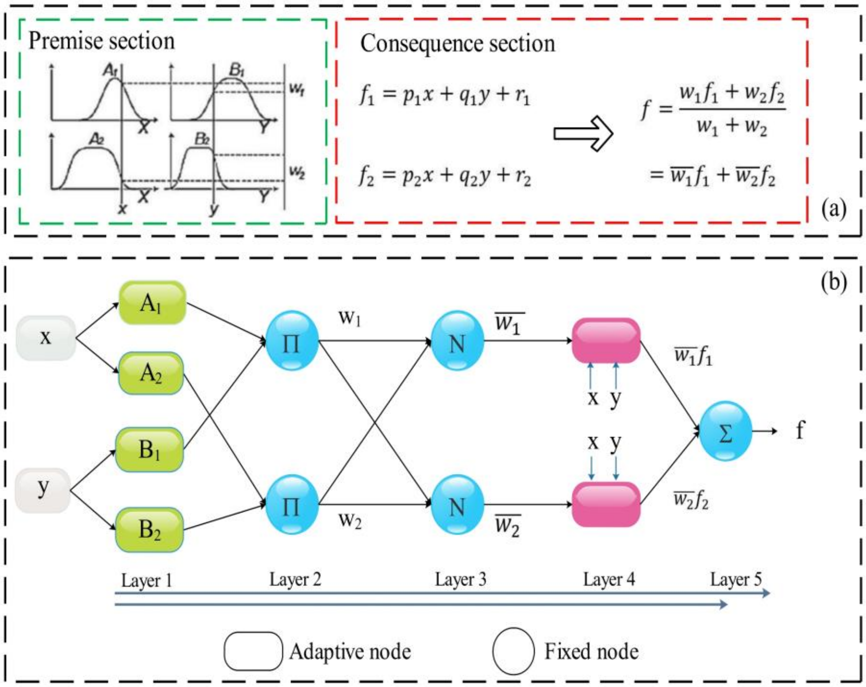


Fig. 6. Architecture of ANFIS

2.2.4. *Hybrid ICA-ANFIS and WOA-ANFIS*

Generally, the two constituent variables of the ANFIS method have a constant and mean input and output membership function [49]. The gradient-based (GB) techniques were commonly applied to adjust the two considered parameters. But, the main defect of this method is that the answer is trapped in the local optimality, which leads to a reduction in the convergence speed [50]. So as to obtain an answer for this problem, different developed algorithms could be applied as a solution [51]–[54]. To gain this aim, the present study applied two optimization algorithms named ICA and WOA (ICA-ANFIS and WOA-ANFIS). The given Fig. 7 presents the training process of this method by mentioned optimizers.

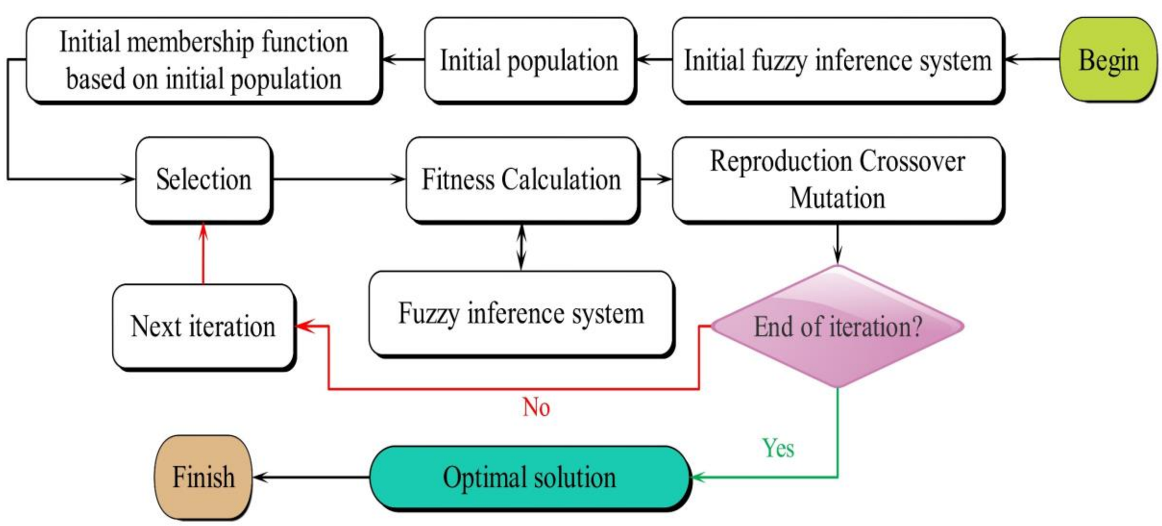


Fig. 7. The flowchart of hybrid ANFIS

2.3. Performance evaluators

Different statistical evaluators were used to appraisal the performance of developed models for predicting the γ_{dmax} and ω_{opt} of lateritic soils. To this purpose, the Coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), relative absolute error (RAE), and root relative squared error (RRSE) were calculated as precision measurements (Eqs. 8-12).

$$SW_i(t+1) = SW_r(t) - GD \quad (8)$$

$$SW_i(t+1) = SW_r(t) - GD \quad (9)$$

$$SW_i(t+1) = SW_r(t) - GD \quad (10)$$

$$SW_i(t+1) = SW_r(t) - GD \quad (11)$$

$$SW_i(t+1) = SW_r(t) - GD \quad (12)$$

where, y_P, t_P, $\bar{t}$, and $\bar{y}$ represent the predicted values of the P^{th} pattern, the target values of the P^{th} pattern, the averages of the target values, and the averages of the predicted values, respectively.

3. Result and discussion

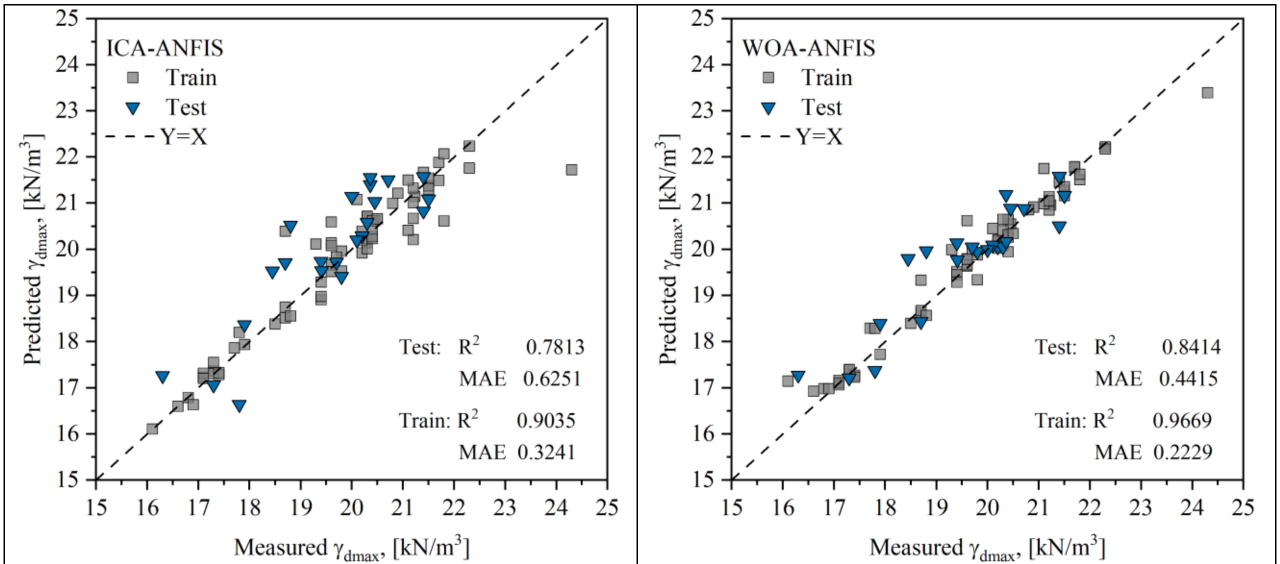
3.1. Results of prediction for γ_{dmax}

The result of proposed models to predict γ_{dmax} related to the standard proctor compaction test of lateritic soils is provided. Here, the hybrid ANFIS models were proposed in order to specify the optimal value of two constituent ANFIS variables, which the ICA and WOA algorithms employed to the ANFIS for this goal. The collected data were divided randomly for training (75%) and testing (25%). The comparison between observed and forecasted ANFIS models is provided in Fig. 8 and Table 2. The provided Fig. 9 presents the result of the ICA-ANFIS and WOA-ANFIS models by representing the histogram plot of errors of γ_{dmax}.

Regarding performance evaluation criteria, in order to have a pervasive comparison of the performance of the models, five indices (R^2, RMSE, MAE, RAE, and RRSE) were evaluated (Table 2). Results present that both models have a reasonable performance in predicting the γ_{dmax} with R^2 larger than 0.9038 for the training data, representing the acceptable correlation between measured and forecasted γ_{dmax}. Regarding developed models, the ANFIS model optimized with WOA has the best performance than the ICA model in both training and testing phases. For example, in the training dataset, the value of R^2, MAE, RMSE, RAE and RRSE is 0.9669, 0.2229, 0.3221, 16.6% and 18.93% for WOA-ANFIS model, while for ICA-ANFIS model are 0.9035, 0.3241, 0.5287, 23.5% and 31.08%, respectively. In the testing phase, the WOA-ANFIS model also outperform ICA-ANFIS, with R^2 (0.8414), MAE (0.4415), RMSE (0.5719), RAE (41.43%) and RRSE (42.25%). All in all, it is clear that WOA-ANFIS can be recognized as the proposed model, which shows its capability in finding the optimal value of two constituent parameters of the ANFIS. Comparing the results of this study with literature show that the results of the proposed WOA-ANFIS model are much better than literature with R^2 at 0.76 [32].

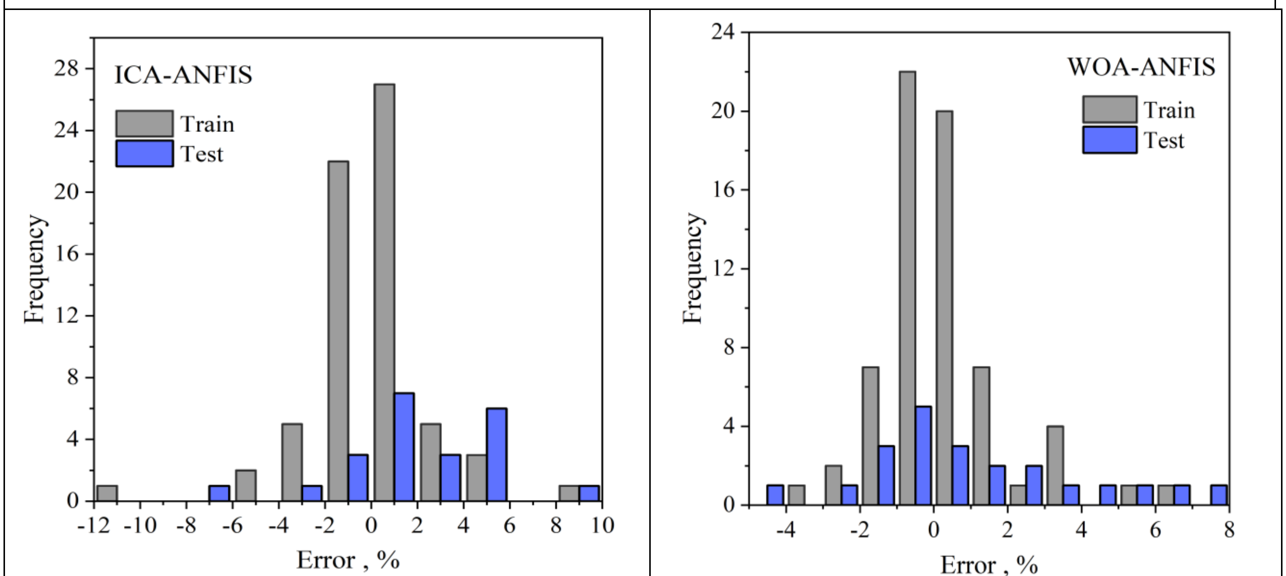
Table 2. The values of performance evaluation indices for γ_dmax

Data category	Index	ICA-ANFIS	WOA-ANFIS	[32]
Training data	R^2	0.9035	0.9669	0.76
	MAE	0.3241	0.2229	
	RMSE	0.5287	0.3221	
	RAE (%)	23.50	16.16	
	RRSE (%)	31.08	18.93	
Testing data	R^2	0.7813	0.8414	
	MAE	0.6251	0.4415	
	RMSE	0.7712	0.5719	
	RAE (%)	58.67	41.43	
	RRSE (%)	56.98	42.25	



(a) (b)

Fig. 8. Scatter plot between measured and predicted values of γ_{dmax}



(a) (b)

Fig. 9. Results of the introduced models in predicting γ_{dmax}

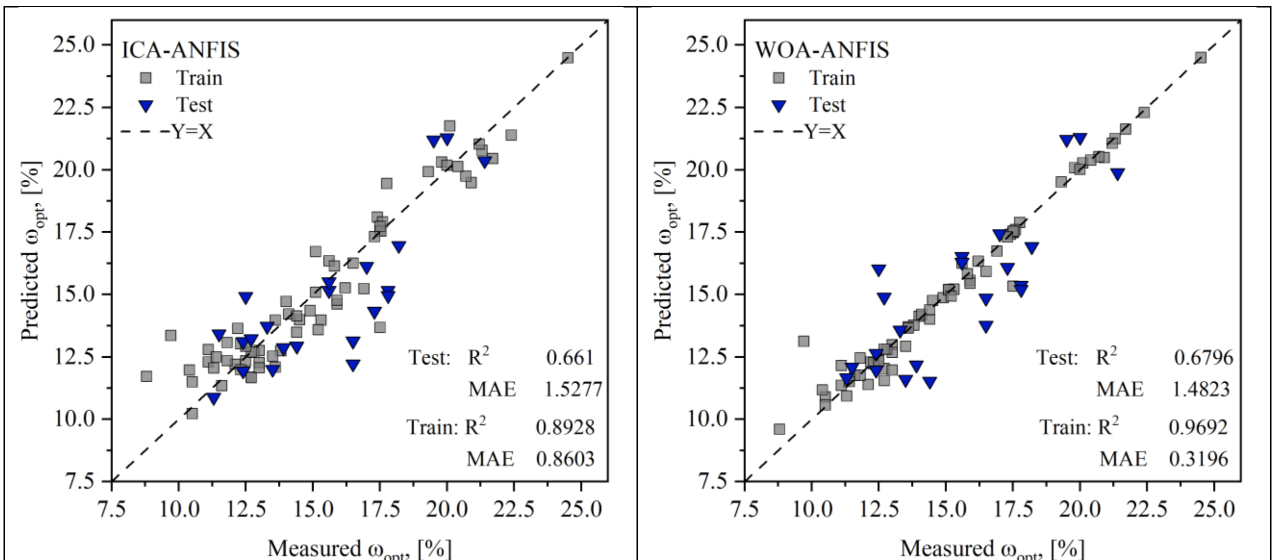
3.2. *Results of prediction for ω_{opt}*

The result of proposed models to predict ω_{opt} related to the standard proctor compaction test of lateritic soils is provided. Here, the hybrid ANFIS models were proposed in order to specify the optimal value of two constituent ANFIS variables, which the ICA and WOA algorithms employed to the ANFIS for this goal. The collected data were divided randomly for training (75%) and testing (25%). The comparison between observed and forecasted ANFIS models is provided in Fig. 10 and Table 3. The provided Fig. 11 presents the result of the ICA-ANFIS and WOA-ANFIS models by representing the histogram plot of errors of ω_{opt}.

Regarding performance evaluation criteria, in order to have a pervasive comparison of the performance of the models, five indices (R^2, RMSE, MAE, RAE, and RRSE) were evaluated (Table 3). Results present that both models have a reasonable performance in predicting the ω_{opt} with R^2 larger than 0.9692 for the training data, representing the acceptable correlation between measured and forecasted ω_{opt}. Regarding developed models, the ANFIS model optimized with WOA has the best performance than the ICA model in both training and testing phases. For example, in the training dataset, the value of R^2, MAE, RMSE, RAE and RRSE is 0.9692, 0.3196, 0.6188, 10.98% and 17.56% for WOA-ANFIS model, while for ICA-ANFIS model are 0.8928, 0.8603, 1.1544, 29.55% and 32.75%, respectively. In the testing phase, the WOA-ANFIS model also outperform ICA-ANFIS, with R^2 (0.6796), MAE (0.1.4823), RMSE (1.7497), RAE (59.31%) and RRSE (60.94%). All in all, it is clear that WOA-ANFIS can be recognized as the proposed model, which shows its capability in finding the optimal value of two constituent parameters of the ANFIS. Comparing the results of this study with literature show that the result of the proposed WOA-ANFIS model is much better than literature with R^2 at 0.707 [32].

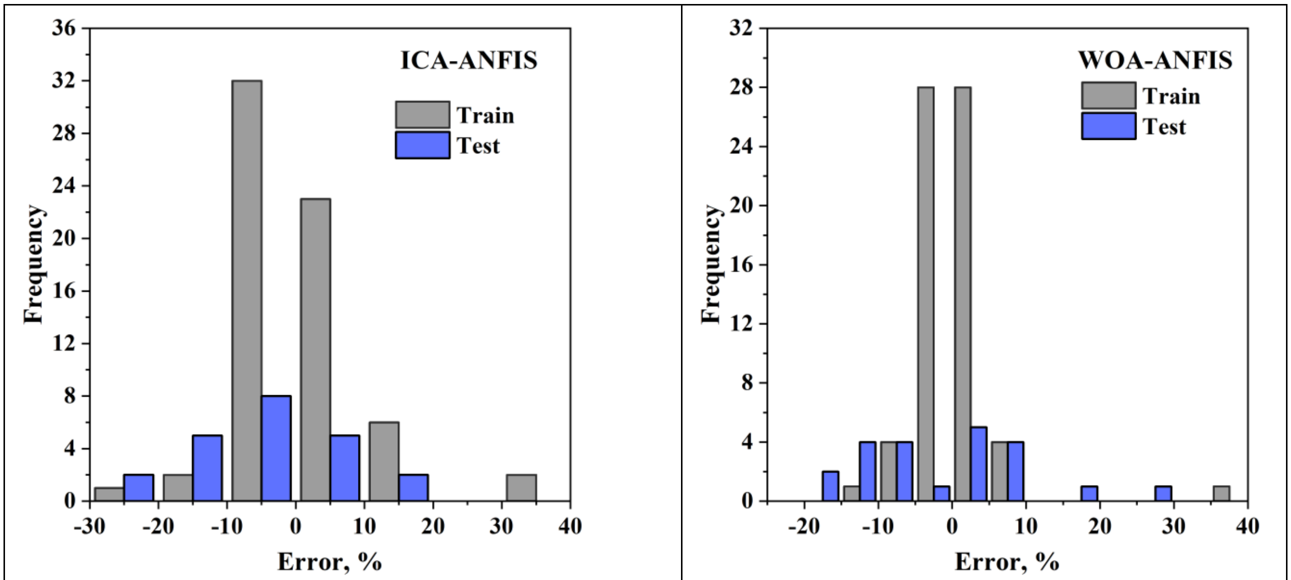
Table 3. The values of performance evaluation indices for ω_opt

Data category	Index	ICA-ANFIS	WOA-ANFIS	[32]
Training data	R^2	0.8928	0.9692	0.707
	MAE	0.8603	0.3196	
	RMSE	1.1544	0.6188	
	RAE (%)	29.55	10.98	
	RRSE (%)	32.75	17.56	
Testing data	R^2	0.661	0.6796	
	MAE	1.5277	1.4823	
	RMSE	1.8813	1.7497	
	RAE (%)	61.13	59.31	
	RRSE (%)	65.52	60.94	



(a) (b)

Fig. 10. Scatter plot between measured and predicted values of ω_{opt}



(a) (b)

Fig. 11. Results of the introduced models in predicting ω_{opt}

4. Conclusion

The main purpose of this study is to scrutinize the applicability of using the hybrid adaptive neuro-fuzzy inference system (ANFIS) models for predicting the maximum dry unit weight (γ_{dmax}) and optimum water content (ω_{opt}) related to standard proctor compaction test of lateritic soils. For the prediction processes, two hybrid ANFIS models were developed, in which two determination variables of the ANFIS method were specified using different optimization algorithms, named imperialist competitive algorithm (ICA) and whale optimization algorithm (WOA). The main results are as follows:

- Results present that both models have a reasonable performance in predicting the γ_{dmax} with R^2 larger than 0.9038 for the training data, representing the acceptable correlation between measured and forecasted γ_{dmax}. Regarding developed models, the ANFIS model optimized with WOA has the best performance than the ICA model in both training and testing phases. For example, in the training dataset, the value of R^2, MAE, RMSE, RAE and RRSE is 0.9669, 0.2229, 0.3221, 16.6% and 18.93% for WOA-ANFIS model, while for ICA-ANFIS model are 0.9035, 0.3241, 0.5287, 23.5% and 31.08%, respectively.
- Results show that both ANFIS models have acceptable performance in predicting the ω_{opt} with R^2 larger than 0.9692 for the training data, recognizing the acceptable correlation between measured and forecasted ω_{opt}. Regarding developed models, the ANFIS model optimized with WOA has the best performance than the ICA model in both training and testing phases.
- Comparing the results of this study with literature show that the result of the proposed WOA-ANFIS model is much better than the literature [32].
- All in all, it is clear that WOA-ANFIS can be recognized as the proposed model, which shows its capability in finding the optimal value of two constituent parameters of the ANFIS.

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