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Maximum dry unit weight and optimum moisture content prediction of lateritic soils using regression analysis

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Highlights

- *Maximum dry unit weight and optimum moisture content prediction*
- *Using multivariate adaptive regression splines for the estimation purpose*
- *Employing different degrees of interactions of models to have precise and reliable outputs*
- *An R^2 of 0.9365 is obtained for the proposed MARS-OI-3 model in the training phase.*
- *In both phases, the value of all criteria for MARS-OI-2 is better than MARS-OI-1.*

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Abstract

Soils compaction with experimental tests is a pivotal facet in the selection of materials for earth constructions. Due to the time limitations and concerns of finishing resources, it is obligate to develop some relationships for predicting compaction parameters such as maximum dry unit weight (γ_{dmax}) and optimum moisture content (ω_{opt}) from easily estimated index properties. The purpose is to evaluate the applicability of multivariate adaptive regression splines (MARS) for estimating γ_{dmax} and ω_{opt} of lateritic soils. Furthermore, different degrees of interactions of models are employed to have comprehensive, precise, and trustable outputs. The outputs of suggested equations to estimate γ_{dmax} related to modified proctor compaction test provide proper capability in the modeling procedure. In the training dataset, the value of all criteria for $\mathrm{MARS-OI-3}$ is proper, with the value of 0.9365, 0.4146, and 93.647 for R^2, RMSE, and VAF, respectively. But testing phase's results are roughly complicated, where scores of $\mathrm{MARS-OI-3}$ equal to 21, bigger than $\mathrm{MARS-OI-2}$ (10) and $\mathrm{MARS-OI-4}$ (17). In summary, $\mathrm{MARS-OI-3}$ outperforms others, where can be known as the suggested equation. The outputs of suggested equations to estimate ω_{opt} also provide great ability in the modeling. In both phases, the value of all criteria for $\mathrm{MARS-OI-2}$ is proper than $\mathrm{MARS-OI-1}$. Also, scores depict that the score of $\mathrm{MARS-OI-2}$ (15) is about double of $\mathrm{MARS-OI-2}$ (9). So, in spite $\mathrm{MARS-OI-1}$ has justifiable usefulness in the forecasting outline, $\mathrm{MARS-OI-2}$ outperforms it.

1. Introduction

The significance of soil compaction cannot be neglected, as the continued depletion of land resources associated with structural development has become more significant in the pursuit of sustainability. The world's populace is developing every time and exists a consistent requirement for the extra foundation such as airplane terminal runways, streets, buildings, wharves, dams, railroads, and so on [1]–[4]. Each of these projects, in the meantime, is built on soil that does not contain sufficient resistance to withstand the loads coming on their way. In Nigeria, the normal laterite soil used for construction may not normally be suitable for its intended use. Therefore, exist a soil improvement requisite which compaction is one of the cheapest and the most common [5], [6].

Lateritic is known as widely improved and circulated air through soils which are created via in-situ weathering and deterioration of rocks under climatic conditions [7]. Expanding utilization of lateritic soil is related to its

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simplicity of getting to, compatibility and density. The compaction of this soil, like other soils, raises its bearing capacity. It reduces the adverse adaptation of buildings constructed on mentioned soils and increases the slopes' stability [8]. The foundations' capacity is widely depended on compaction properties, where is determined by indicating the maximum dry weight (γ_{dmax}) of the optimum moisture content (ω_{opt}) in the specified energy.

Numerous articles have depicted the prosperous use of artificial intelligence-based techniques in the branches of engineering [9]–[16]. Experimental connections were suggested sometimes based on computational methods such as regression [17]–[20]. In addition to the fact that there are many factors in the compaction parameters of effectiveness, as proposed by [21], roughly all empirical connections developed from statistical methods such as regression might contain various deviations. However, this opinion does not seem to be a good reason. Among other works, Ardakani and Kordnaeij [21] engaged the genetic model usage as well as ANN for extending analogous connections to estimate ω_{opt} and γ_{dmax}. Zhu et al., was developed the SVR models for predicting the compaction properties of lateritic soils [22]. Other study engaged an evolutionary polynomial regression to suggest some models to estimate ω_{opt} and γ_{dmax} [23], while lately an estimating algorithm extended for in-situ γ_d from penetrometer trials in chamber of calibration.

MLP neural network was applied for precise extending models for γ_{dmax} and ω_{opt} of modified soil. The improved artificial neural network was created for extending clear formulations of γ_{dmax} and ω_{opt}. The outputs indicate that the suggested models' accuracy is considerable in comparison with the observations [24]. Linear regression methods in logarithmic form were proposed for evaluating the γ_{dmax} and ω_{opt} of the fine-grained soil. So, concluded system through regression analysis could be employed for estimating the both γ_{dmax} and ω_{opt}. For predicting γ_{dmax} and ω_{opt}, some parameters were included in the best model named compaction energy, specific gravity, liquid limit, and also grain size [25]. Another article purposed for extending empirical formulas between γ_{dmax} and ω_{opt} with compaction energy in logarithm form and ratio of sand for lateritic soils [26].

The objective of this article is to evaluate the usefulness of the regression method of the multivariate adaptive regression splines (MARS) for estimating the compaction properties of lateritic soils (maximum dry unit weight (γ_{dmax}) and optimum water content (ω_{opt})), which could be utilized in practical projects. Furthermore, several degrees of interaction are suggested to have precise and reliable outputs. To the estimation outline, six variables were taken into account as inputs, such as percent of fines (FC), gravel content (G), sand content (S), liquid limit (ω_l), plastic limit (ω_p), and plasticity index (I_p).

2. Methodology

2.1. Description of the Dataset

To design the estimation procedure of γ_{dmax} and ω_{opt} for the modified proctor compaction test, a collection of records was collected from the Tailings Storage Facility dam in Tarkwa, Ghana (Figs. 1 and 2) [27], that was separated into training and testing phase by proportion of 0.75 and 0.25. The prevailing soil is lateritic observed in numerous locations of Africa. Fresh soils samples were collected from the depth of 0.3 to 2 meters during the dam construction. These samples were tested under particle size analysis [28], Atterberg limit [29], and modified proctor compaction tests [30]. To the modeling development, six parameters were entered 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) [27]. The supplied Table 1 show the statistics of variables used.

The relationship between inputs could be evaluated by the Pearson Correlation Coefficient [31]. PCC matrix is plotted for ω_{opt} and γ_{dmax} in Fig. 3. A high amount could conclude in difficulties in interpreting the impressions of the parameters on the conclusions. Regarding ω_{opt} PCC values, Fig. 3a supply a big value of the correlation between any two variables are rather low (i.e., lower than 0.458), cause that might not lead to multicollinearity problems [32]. Moreover, the biggest negative and positive value is between ω_{opt} and I_p at -0.814, and between I_p and ω_l at 0.854. Turning to γ_{dmax} (Fig. 3b), the largest negative and positive value is between FC and S at -0.766, and between I_p and ω_l at 0.854.

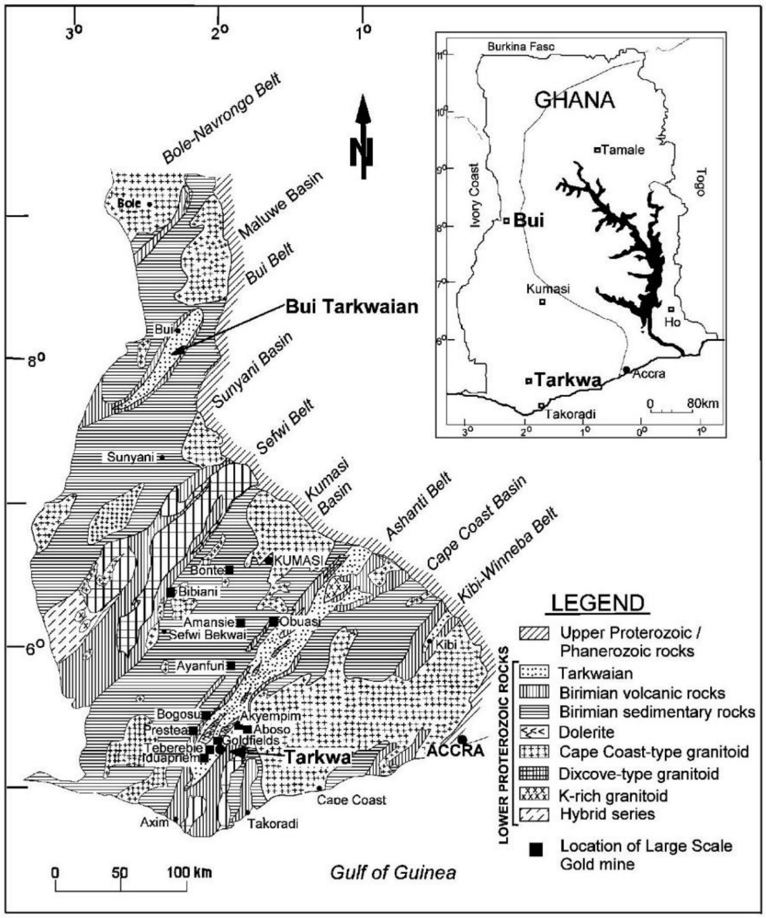


Fig. 1. Simplified geological map of southwest Ghana [33]

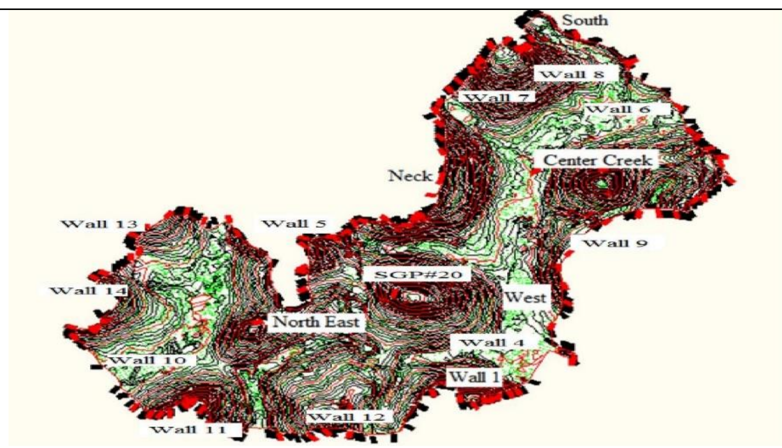
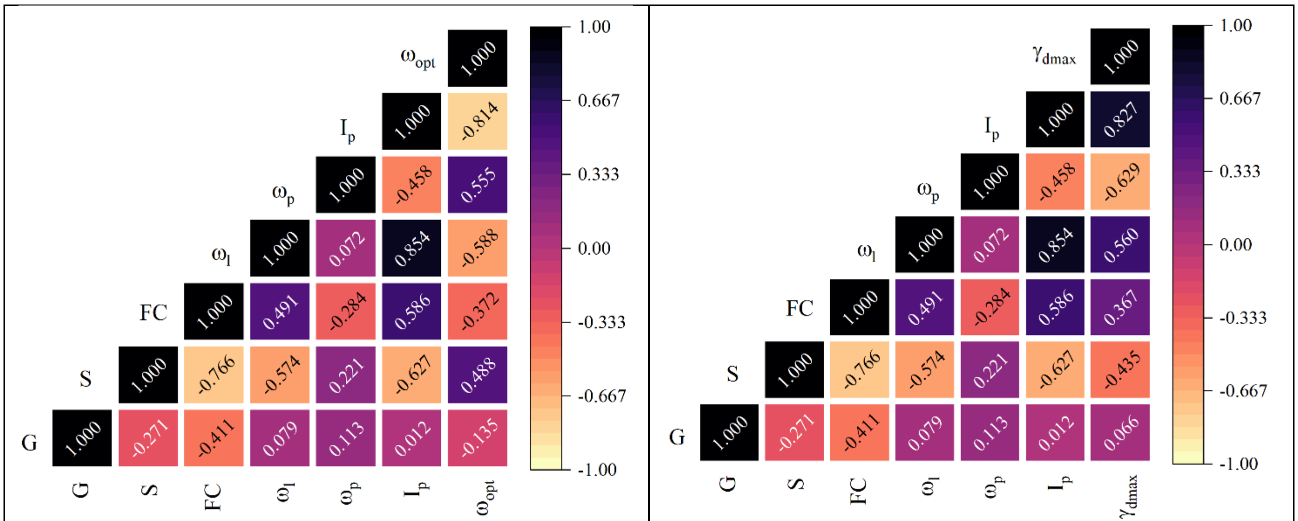


Fig. 2. Site layout of the TSF dam, Tarkwa [27]

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	0.6	11	12.9	24.4	11.8	1.08	6.7	19.08

Maximum	45	86.5	80.18	64	32.7	41	14.5	25.62
St. deviation	11.9115	18.385	17.998	10.013	5.2396	10.883	1.9878	1.6448
Average	15.642	39.331	45.0261	47.527	21.574	25.964	9.89625	22.726
Median	11.7	38.22	43.225	47.63	21.055	28.95	9.7825	22.85
Skewness	0.895	0.3554	0.25	-0.22	0.3157	-0.841	0.499	-0.445
Kurtosis	-0.1366	-0.805	-0.976	-0.903	-0.628	-0.214	-0.545	-0.3666
Testing data								
Minimum	1.9	13.3	10.05	19	11	0.81	6.3	19.34
Maximum	43.7	60.95	75.6	62.81	39.24	37.84	13.7	25.1
St. deviation	14.265	14.776	21.017	9.899	7.374	12.103	2.059	1.681
Average	19.0995	31.041	49.8605	46.507	21.404	25.103	9.1845	23.1875
Median	20.5	23.75	49.4	49.6	19.25	29.785	8.7	23.7
Skewness	0.1567	0.996	-0.5035	-0.932	1.2193	-1.058	0.9533	-1.303
Kurtosis	-1.5198	-0.286	-0.782	1.516	1.0781	-0.162	0.0635	0.769



(a) (b)

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

2.2. *Multivariate Adaptive Regression Splines (MARS)*

MARS is a regression method that is utilized for a large diversity of engineering issues, and it was defined by Jerome Harold Friedman [34]. Multivariate adaptive regression splines recognize as a non-parametric regression algorithm which can generate non-linear models and model the interplays among parameters [35]. MARS has been largely utilized in several scopes like hydrology [36], energy performance [37], ergonomics [38], transportation [39], geotechnical engineering [40], [41], building engineering [42], biological networks [43], and so forth since its advent in 1991 [34].

MARS is able to describe the practical relevance among the independent and dependent variables. The spline that recognizes as a continuous piecewise-defined polynomial is this algorithm's kernel [38]. The MARS regression model contains two parts [35], like the testing and training part. In the MARS's forward step, the fundamental functions are joined frequently that chosen from the apperceived dataset spontaneously and generate the biggest model with plenty of fundamental functions. Nevertheless, this model may be overfitted because the backward step is utilized to reduce the convolution by fundamental functions removal that leads to a little increment in the residual squared error [43]. The following equation explains the MARS model [40]:

$$f\ (x) = \sum_{i=1}^{n} c_i B_i(x) \tag{1}$$

x	An independent parameter
$B_i(x)$	The basis function
N	Number of terms
c_i	The least-square method estimation coefficient

The fundamental functions $\left(B_i(x)\right)$ are represented as bellow [42], [43]:

$$B_i(x) = \begin{cases} x \; if \; x \geq 0 \\ 0 \; otherwise \end{cases} \tag{2}$$

The generalized cross-validation (GCV) is used for specifying that fundamental functions are preoccupied in the model [38]. The generalized cross-validation is calculationally less costly than the various methods. The GCV equation is represented as below, by the division of mean squared residual error upon a penalty [41], [42]:

$$GCV = \frac{1}{N}\sum_{i=1}^{N}[y_i - f(x_i)]^2 \Big/ \left[1 - \frac{M = d \times (M-1)/2}{N}\right]^2 \tag{3}$$

M	the number of basic functions
N	the number of data points
d	he penalizing parameter
$(M-1)/2$	The least-square method estimation coefficient
$f(x_i)$	the predicted value

2.3. *Performance criteria*

Some evaluators were calculated to evaluate the accuracy of predicting models such as Coefficient of determination (R^2), root mean squared error ($RMSE$), the variance accounted factor (VAF), and mean absolute error (MAE) (Eqs. (4)- (7)).

$$R^2 = \left(\frac{\sum_{p=1}^{P}(t_P - \bar{t})(y_P - \bar{y})}{\sqrt{\left[\sum_{p=1}^{P}(t_P - \bar{t})^2\right]\left[\sum_{p=1}^{P}(y_P - \bar{y})^2\right]}}\right)^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{P}\sum_{p=1}^{P}\left(y_p - t_p\right)^2} \tag{5}$$

$$MAE = \frac{1}{P}\sum_{p=1}^{P}\left|y_p - t_p\right| \tag{6}$$

$$VAF = \left(1 - \frac{var(t_P - y_P)}{var(t_P)}\right) * 100 \tag{7}$$

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

3. Result and discussion

3.1. Results of prediction for γ_{dmax}

The information of the basic functions and suggested relations are presented in Table 2 for the order of interactions (OI) of 2, 3, and 4 equations $(\mathrm{MARS-OI-2, MARS-OI-3}$ and $\mathrm{MARS-OI-4})$. The MARS method different orders formulations for forecasting the γ_{dmax} related to modified proctor compaction tests are supplied in Eqs. (8-10). Basis functions of $\mathrm{MARS-OI-2, MARS-OI-3}$, and $\mathrm{MARS-OI-4}$ were estimated from 3 to 40. By raising the order of interactions from 2 to 3, the values of R^2 changed from 0.8985 to 0.9365 but reduced to 0.9285 by increasing the OI to 4.

$MARS - OI - 2$:

$$\gamma_{dmax} = 21.863 + 0.227 \times BF1 - 0.163 \times BF2 - 4.312e -3 \times BF3 + 0.0222 \times BF4 - 0.04041 \times BF5 + 0.07455 \times BF6 - 0.0272 \times BF7 + 4.309e - 3 \times BF8 \tag{8}$$

$MARS - OI - 3$:

$$\gamma_{dmax} = 21.778 + 0.19299 \times BF1 - 0.2047 \times BF2 - 8.374e - 3 \times BF3 + 0.01595 \times BF4 + 1.396e - 3 \times BF5 + 3.073e - 3 \times BF6 + 0.019576 \times BF7 + 0.0265 \times BF8 + 2.546e - 3 \times BF9 - 5.657e - 4 \times BF10 - 6.4332e - 4 \times BF11 \tag{9}$$

$MARS - OI - 4$:

$$\gamma_{dmax} = 22.54 + 0.1675 \times BF1 - 0.159 \times BF2 - 9.891e - 3 \times BF3 + 5.1528e - 3 \times BF4 + 1.92e - 3 \times BF5 + 2.367e - 2 \times BF6 - 1.2116e - 1 \times BF7 - 0.1336e - 1 \times BF8 + 1.985e - 3 \times BF9 - 1.1632e - 4 \times BF10 - 1.99e - 4 \times BF11 \tag{10}$$

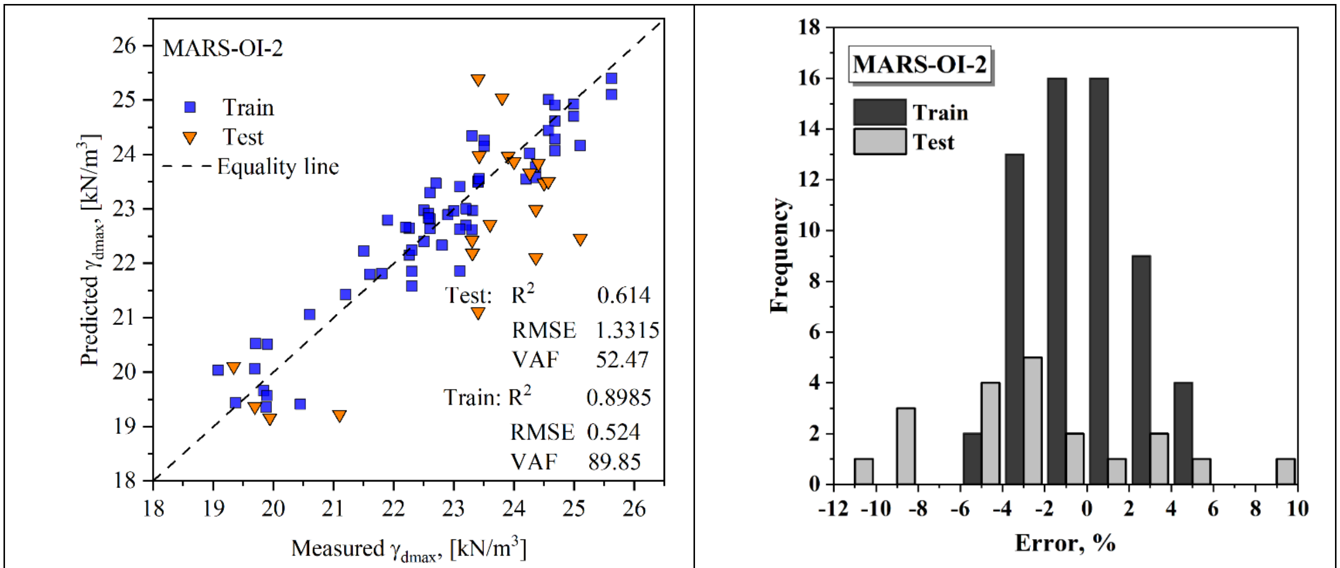
Table 2. Simulation results of a basic system.

BF	Equation		
	MARS-OI-2 (Eq. 8)	MARS-OI-3 (Eq. 9)	MARS-OI-4 (Eq. 10)
BF1	$max(0, I_p - 21.7)$	$max(0, I_p - 21.7)$	$max(0, I_p - 21.7)$
BF2	$max(0, 21.7 - I_p)$	$max(0, 21.7 - I_p)$	$max(0, 21.7 - I_p)$
BF3	$max(0, FC - 48.3) \times BF1$	$max(0, FC - 48.3) \times BF1$	$max(0, FC - 48.3) \times BF1$
BF4	$max(0, S - 24.3)$	$max(0, 48.3 - FC) \times BF1$	$max(0, \omega_p - 22.04) \times BF3$
BF5	$max(0, \omega_l - 18.3) \times BF1$	$max(0, \omega_p - 22.04) \times BF3$	$max(0, 22.04 - \omega_p) \times BF3$
BF6	$max(0, \omega_p - 22.2) \times BF1$	$max(0, 22.04 - \omega_p) \times BF3$	$max(0, S - 24.3)$
BF7	$max(0, 24.3 - S) \times max(0, \omega_l - 47.6)$	$max(0, S - 24.3)$	$max(0, \omega_p - 18.3)$
BF8	$max(0, 37.8 - S) \times BF1$	$max(0, 24.75 - \omega_p) \times BF2$	$max(0, 18.3 - \omega_p)$
BF9		$\max(0, 38.6 - \omega_l) \times \max(0, \omega_p - 24.75) \times BF2$	$\max(0, 38.6 - \omega_l) \times \max(0, \omega_p - 24.75) \times BF2$
BF10		$max(0, \omega_l - 24.4) \times BF4$	$\max(0, 48.3 - FC) \times \max(0, \omega_l - 24.4) \times BF1$
BF11		$max(0, 24.4 - S) \times BF3$	$max(0, 37.8 - S) \times BF4$

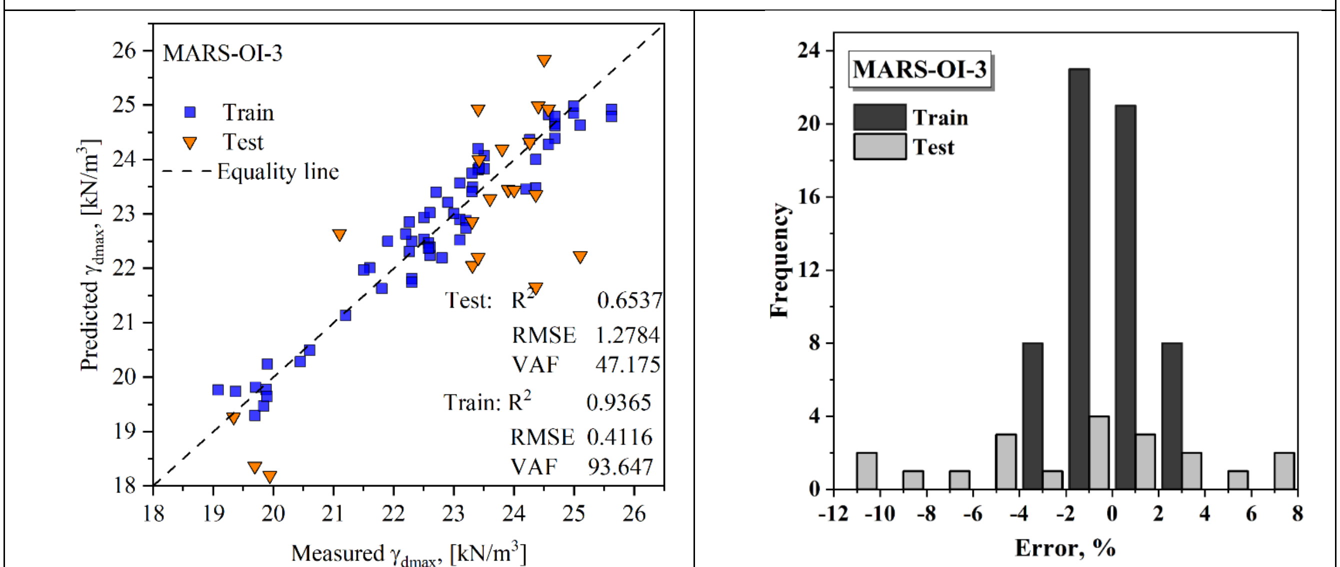
The performance of suggested formulations for estimating γ_{dmax} for modified proctor compaction test of lateritic soils is as below. Fig. 4 shows proper capability in the modeling procedure. To assess the accuracy of developed models, indices were computed, such asR^2,RMSE, MAE, and VAF. Furthermore, scores were allocated to the criteria, where the summation of scores could be determined the most proper model. In the training data set, all indices for $\mathrm{MARS-OI-3}$ is proper compared to others, at 0.9365, 0.4146, 0.3484, and 93.647 forR^2,RMSE,MAE, and VAF, respectively. But, the criteria in the testing data set are somewhat complex. Here, scores could be beneficial, where the score of $\mathrm{MARS-OI-3}$ is 21, bigger than $\mathrm{MARS-OI-2}$ (10) and $\mathrm{MARS-OI-4}$ (17). All in all, although other orders of MARS have acceptable performance in the predicting process, $\mathrm{MARS-OI-3}$ outperforms these equations, which can be recognized as the proposed equation.

Table 3. The results of developed MARS models for γ_dmax

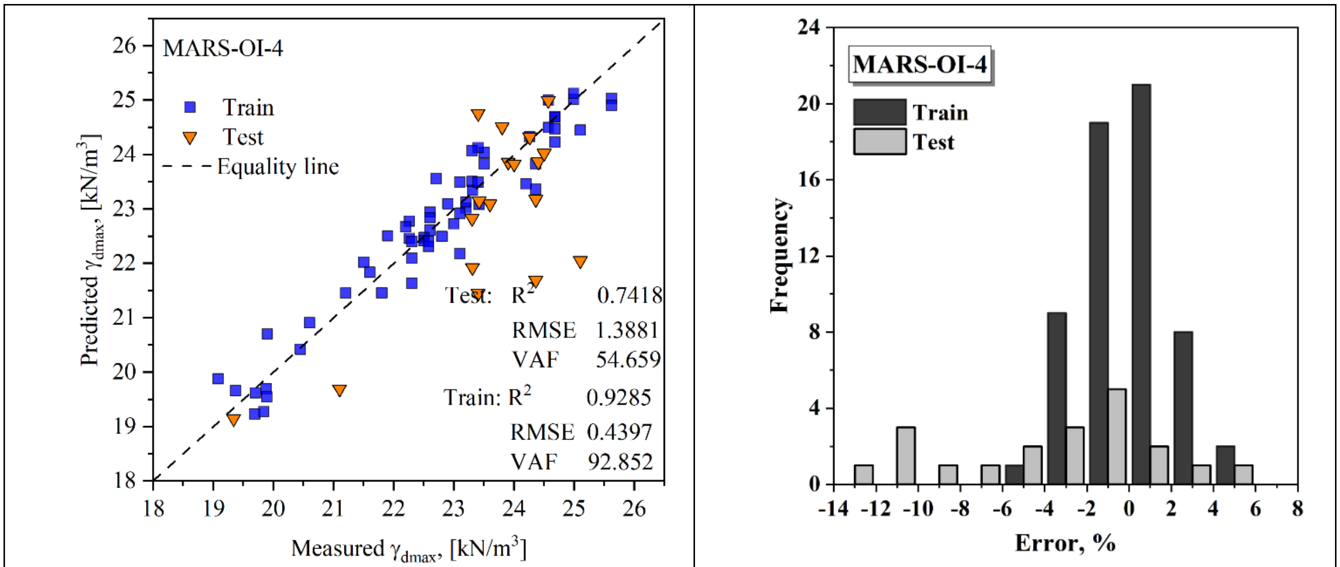
Models		**MARS-OI-2**	**MARS-OI-3**	**MARS-OI-4**	[27]
Number of basis function		13	24	23	
Training phase	R2	0.8985	0.9365	0.9285	0.76
	Rank for R2	1	3	2	
	RMSE	0.524	0.4146	0.4397	
	Rank for RMSE	1	3	2	
	MAE	0.428	0.3484	0.3528	
	Rank for MAE	1	3	2	
	VAF	89.8497	93.647	92.8524	
	Rank for VAF	1	3	2	
Testing phase					
	R2	0.6138	0.6537	0.7418	
	Rank for R2	1	2	3	
	RMSE	1.3315	1.2784	1.3881	
	Rank for RMSE	2	3	1	
	MAE	1.1197	1.0172	1.0589	
	Rank for MAE	1	3	2	
	VAF	52.4764	47.1751	54.6594	
	Rank for VAF	2	1	3	
Score		10	21	17	


MARS-OI-2
Train
Test
Equality line
Test: R^2 0.614
RMSE 1.3315
VAF 52.47
Train: R^2 0.8985
RMSE 0.524
VAF 89.85
Predicted γ_{dmax}, [kN/m^3]
Measured γ_{dmax}, [kN/m^3]
MARS-OI-2
Train
Test
Frequency
Error, %

(a)


MARS-OI-3
Train
Test
Equality line
Test: R^2 0.6537
RMSE 1.2784
VAF 47.175
Train: R^2 0.9365
RMSE 0.4116
VAF 93.647
Predicted γ_{dmax}, [kN/m^3]
Measured γ_{dmax}, [kN/m^3]
MARS-OI-3
Train
Test
Frequency
Error, %

(b)



(c)

Fig. 4. The scatter plot between measured and predicted γ_{dmax}, and Error distribution histogram

3.2. Results of prediction for ω_{opt}

The information of the basic functions and suggested relations are presented in Table 4 for the order of interactions (OI) of 1 and 2 equations ($\mathrm{MARS-OI-1}$ and $\mathrm{MARS-OI-2}$). The MARS method different orders formulations for forecasting the ω_{opt} related to modified proctor compaction tests are supplied in Eqs. (11 and 12). Basis functions of $\mathrm{MARS-OI-1}$ and $\mathrm{MARS-OI-2}$ were estimated from 3 to 30. By raising the OI from 1 to 2, the values of R^2 changed from 0.7957 to 0.8662. Moreover, $RMSE$ presents a decline from 0.8985 to 0.7272.

$MARS-OI-1$:

$$\omega_{opt} = 8.1287 + 0.04787 \times BF1 + 0.2107 \times BF2 - 0.1607 \times BF3 + 0.1476 \times BF4 \tag{11}$$

$MARS-OI-2$:

$$\omega_{opt} = 8.445 + 0.2268 \times BF1 - 0.113 \times BF2 - 0.0316 \times BF3 - 4.85e - \times BF4 + 8.6713e - 3 \times BF5 \tag{12}$$

Table 4. Basis functions and related equations of regression approach for ω_opt

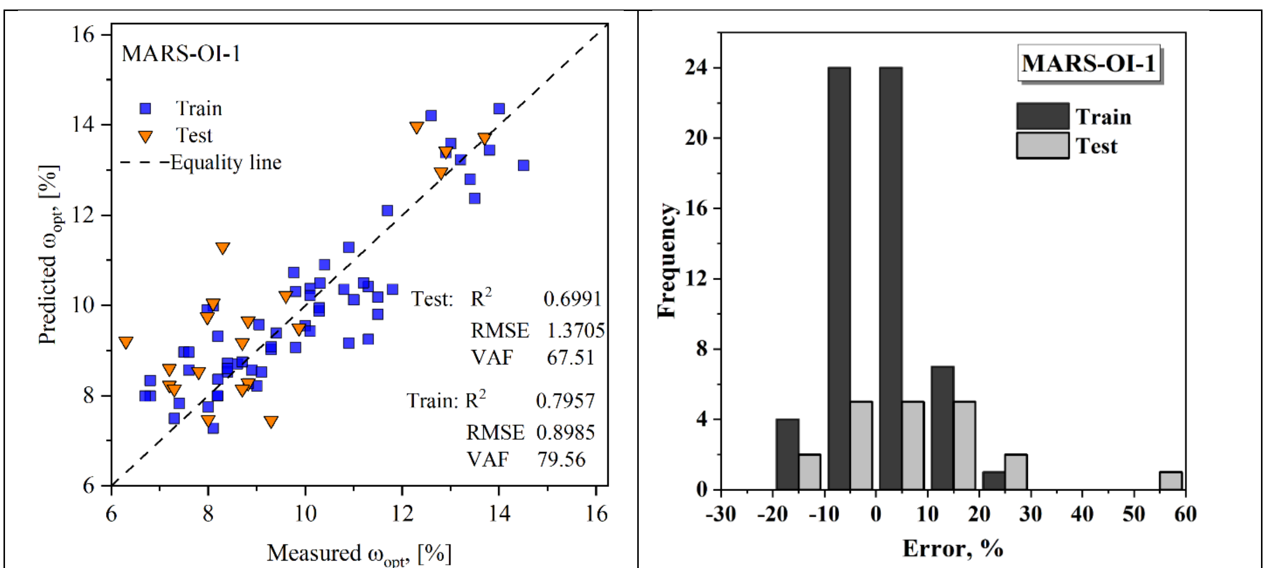
BF	Equation	
	MARS-OI-1 (Eq. 11)	MARS-OI-2 (Eq. 12)
BF1	$max(0, FC - 53.1)$	$max(0, 30.6 - I_p)$
BF2	$max(0, 51.48 - \omega_l)$	$max(0, \omega_p - 23.37) \times max(0, I_p - 30.6)$
BF3	$max(0, 22.2 - \omega_p)$	$max(0, 23.37 - \omega_p) \times max(0, I_p - 30.6)$
BF4	$max(0, \omega_p - 18.3)$	$max(0, 41.9 - FC) \times max(0, 47.63 - \omega_l)$
BF5		$max(0, FC - 48.3) \times max(0, \omega_l - 47.63)$

The performance of suggested formulations for estimating ω_{opt} for modified proctor compaction test of lateritic soils is as below. Fig. 5 shows proper capability in the modeling procedure. To assess the accuracy of developed models, indices were computed, such as R^2, RMSE, MAE, and VAF. Furthermore, scores were allocated to the criteria, where the summation of scores could be determined the most proper model. In both the training and testing phase, the value of all criteria for $\mathrm{MARS-OI-2}$ is better than $\mathrm{MARS-OI-1}$, with a small exception of VAF in the testing phase. For example, in the training phase, the value of R^2, RMSE, MAE, and VAF are 0.8662, 0.7272, 0.5821, and 86.617 for $\mathrm{MARS-OI-2}$, respectively, better than their values for $\mathrm{MARS-OI-1}$. Also, the same trend persists in the testing dataset, with the exception of VAF. As well, summated scores show that the score of $\mathrm{MARS-OI-2}$ (15) is roughly double than $\mathrm{MARS-OI-2}$ (9). All in all, although $\mathrm{MARS-OI-1}$ has acceptable performance in the predicting process, MARS – OI – 1 outperforms this equation, which can be recognized as the proposed equation.

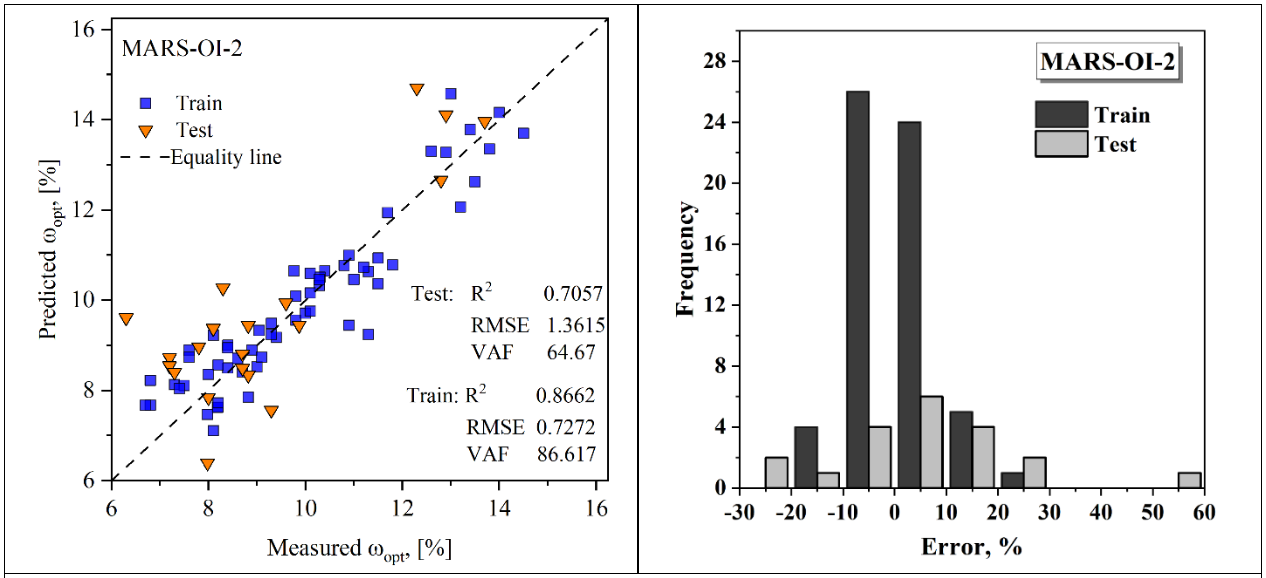
The performance of suggested formulations for estimating γ_{dmax} for modified proctor compaction test of lateritic soils is as below. Fig. 4 shows proper capability in the modeling procedure. To assess the accuracy of developed models, indices were computed, such as R^2, RMSE, MAE, and VAF. Furthermore, scores were allocated to the criteria, where the summation of scores could be determined the most proper model.

Table 5. The results of developed MARS models for ω_opt

Models		MARS-O1	MARS-O2	[27]
Number of basis function		4	9	
Training phase	R^2	0.7957	0.8662	0.707
	Rank for R^2	1	2	
	RMSE	0.8985	0.7272	
	Rank for RMSE	1	2	
	MAE	0.7126	0.5821	
	Rank for MAE	1	2	
	VAF	79.5673	86.6172	
	Rank for VAF	1	2	
Testing phase				
	R^2	0.6991	0.7057	
	Rank for R^2	1	2	
	RMSE	1.3705	1.3615	
	Rank for RMSE	1	2	
	MAE	1.0908	1.0692	
	Rank for MAE	1	2	
	VAF	67.5102	64.6733	
	Rank for VAF	2	1	
Score		9	15	



(a)



(b)

Fig. 5. The scatter plot between measured and predicted ω_{opt}, and Error distribution histogram

4. Conclusions

The objective of this article is to evaluate the usefulness of the regression method of the multivariate adaptive regression splines (MARS) for estimating the compaction properties of lateritic soils (maximum dry unit weight (γ_{dmax}) and optimum water content (ω_{opt})), which could be utilized in practical projects. Furthermore, several degrees of interactions are suggested to have precise and reliable outputs. The main results are as follows:

The performance of suggested formulations for estimating γ_{dmax} for modified proctor compaction test of lateritic soils shows proper capability in the modeling procedure. In the training data set, all indices for $\mathrm{MARS}-\mathrm{OI}-3$ is proper compared to others, at 0.9365, 0.4146, 0.3484, and 93.647 for R^2, RMSE, MAE, and VAF, respectively. But, the criteria in the testing data set are somewhat complex. All in all, although other orders of *MARS* have acceptable performance in the predicting process, $\mathrm{MARS}-\mathrm{OI}-3$ outperforms these equations, which can be recognized as the proposed equation.

The performance of suggested formulations for estimating ω_{opt} for modified proctor compaction test of lateritic soils shows proper capability in the modeling procedure. In both the training and testing phase, the value of all criteria for $\mathrm{MARS}-\mathrm{OI}-2$ is better than $\mathrm{MARS}-\mathrm{OI}-1$, with a small exception of VAF in the testing phase. As well, summated scores show that the score of $\mathrm{MARS}-\mathrm{OI}-2$ (15) is roughly double than $\mathrm{MARS}-\mathrm{OI}-2$ (9). All in all, although $\mathrm{MARS}-\mathrm{OI}-1$ has acceptable performance in the predicting process, $\mathrm{MARS}-\mathrm{OI}-1$ outperforms this equation, which can be recognized as the proposed equation.

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