

# Ensemble deep learning-based models to predict the resilient modulus of modified base materials subjected to wet-dry cycles

Mahzad Esmaeili-Falak\*<sup>1</sup> and Reza Sarkhani Benemaran<sup>2</sup>

<sup>1</sup>Department of Civil Engineering, North Tehran Branch, Islamic Azad University, Tehran, Iran

<sup>2</sup>Department of Civil Engineering, Faculty of Geotechnical Engineering, University of Zanjan, Zanjan, Iran

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**Abstract.** The resilient modulus ( $M_R$ ) of various pavement materials plays a significant role in the pavement design by a mechanistic-empirical method. The  $M_R$  determination is done by experimental tests that need time and money, along with special experimental tools. The present paper suggested a novel hybridized extreme gradient boosting (XGB) structure for forecasting the  $M_R$  of modified base materials subject to wet-dry cycles. The models were created by various combinations of input variables called deep learning. Input variables consist of the number of W-D cycles (WDC), the ratio of free lime to SAF (CSAFR), the ratio of maximum dry density to the optimum moisture content (DMR), confining pressure ( $\sigma_3$ ), and deviatoric stress ( $\sigma_d$ ). Two XGB structures were produced for the estimation aims, where determinative variables were optimized by particle swarm optimization (PSO) and black widow optimization algorithm (BWOA). According to the results' description and outputs of Taylor diagram, M1 model with the combination of WDC, CSAFR, DMR,  $\sigma_3$ , and  $\sigma_d$  is recognized as the most suitable model, with  $R^2$  and RMSE values of BWOA-XGB for model M1 equal to 0.9991 and 55.19 MPa, respectively. Interestingly, the lowest value of RMSE for literature was at 116.94 MPa, while this study could gain the extremely lower RMSE owned by BWOA – XGB model at 55.198 MPa. At last, the explanations indicate the BWO algorithm's capability in determining the optimal value of XGB determinative parameters in  $M_R$  prediction procedure.

**Keywords:** extreme gradient boosting; modified base materials; predicting; resilient modulus; wet-dry cycles

## 1. Introduction

The Resilient modulus ( $M_R$ ), is one of the well-recognized stress-based parameters that engineers have widely used today to investigate the elastic characteristics of subgrade. The two references used by engineers for resilient modulus-based analysis and design are AASHTO (AASHTO T-307, 2017) pavement design manual and the Mechanistic-Empirical Pavement Design Guide (MEPDG) (NCHRP, 2004). The resilient modulus of subgrade is also accepted by these manuals as a material characteristic to analyze and design the pavement. Investigating the literature review clearly demonstrates the significant effect of resilient modulus on the designed pavement properties, especially its thickness. The following simple equation has been widely used to determine the resilient modulus.

$$M_R = \frac{\sigma_d}{\varepsilon_r} \quad (1)$$

where,  $\sigma_d$  and  $\varepsilon_r$  are the maximum value of the deviatoric stress and the reversible strain, respectively. In simple terms, for a pavement which is under traffic load, the slope of the stress-strain curve at the unloading step demonstrates the resilient modulus.

Treated subgrade materials consist of water, natural or

artificial aggregates, cement-based materials, and admixtures (Aghayari Hir *et al.* 2022, Cemiloglu *et al.* 2023, Chen *et al.* 2020, Ding *et al.* 2021, Esmaeili-Falak *et al.* 2020, Esmaeili-Falak *et al.* 2018, Esmaeili Falak and Sarkhani Benemaran 2022, Ge *et al.* 2022, Kalantari *et al.* 2011, Lu *et al.* 2021, Ma *et al.* 2020, Moayed and Janbaz 2011, Moradi *et al.* 2022, Mukiza *et al.* 2019, Nanehkaran *et al.* 2023, Nikpeyman *et al.* 2022, Nwonu and Ikeagwuani 2021; Sarkhani Benemaran, *et al.* 2022, Shi *et al.* 2023).

Fatigue-based failures of binder and Topeka layers can be reduced using stabilizing materials because of their high stiffness specifications. The stabilized subgrade should be designed and performed in such a way that it can reasonably bear environmental conditions like freeze-thaw and wet-dry cycles. On the other hand, considerable relations have been proved between the various environmental conditions and the introduced resilient modulus. Previously conducted research demonstrated that cement-based stabilizers had been strengthened subgrade resilient modulus against the durability specifications, especially the wet-dry cycles (Addison and Polma 2007, Amadi 2014, Bandara *et al.* 2015, Coban and Cetin 2022, Ifediniro and Ekeocha 2022, Khalife *et al.* 2012, Onyelowe and Duc 2020, Solanki *et al.* 2013, Tiwari *et al.* 2021, Tiwari and Satyam 2021, Wang *et al.* 2021, Wang *et al.* 2019, Zhang and Tao 2008).

In addition to utilizing the experimental tests and back-analysis procedure to determine the resilient modulus, recently, novel data mining-based approaches have emerged to estimate the precise amounts of the resilient modulus. Due to the high simplicity and accuracy of laboratory

\*Corresponding author, Assistant Professor  
E-mail: m.esmaeilifalak@iau-tnb.ac.ir

results to determine the resilient modulus of the subgrade soil and also because of the sufficient number of databases, the application of soft computing (Benemaran and Esmaili-Falak 2020, Esmaili-Falak *et al.* 2019, Yang *et al.* 2022, Yuan *et al.* 2022, Zhu *et al.* 2022) in predicting the resilient modulus has led to acceptable results and reasonable accuracy (Camarena 2021, Fedakar 2021, Fouad *et al.* 2022, Ghorbani *et al.* 2020, Heidariapanah *et al.* 2017, Ikeagwuani *et al.* 2021, Kayadelen *et al.* 2021, Nazzal and Tatari 2013, Sadrossadat *et al.* 2016, Solanki *et al.* 2009, Tarawneh and Nazzal 2014, Zaman *et al.* 2010, Zou *et al.* 2021).

The first soft-computing-based studies in order to estimate the amounts of resilient modulus are related to the application of regression-based models. In a study, a regression-based approach has been proposed to estimate the resilient modulus of a stabilized subgrade using the value of wet-dry cycles, cement-based materials constituents, physical specifications of the admixtures, and the level of stress. This approach defined the resilient modulus as a function of wet-dry cycles, cement-based materials constituents, *DMR* factor (which is defined as the maximum dry unit weight to the optimum water content), confining, and deviatoric stresses (Khoury and Zaman 2007). In the following, the results of Maalouf *et al.* (2012) demonstrated that the support vector regression estimations have more accuracy than that of the simple regression and least square approaches.

With the advancement of the Artificial Intelligence (*AI*)-based approaches in the field of civil and geotechnical engineering, and considering the high accuracy of the predictions using these techniques, their application in predicting resilient modulus and other fields also expanded. The first application of *AI*-based models to estimate the resilient modulus of stabilized subgrade under wet-dry cycles condition is conducted by Ghanizadeh and Rahrovan (Ghanizadeh and Rahrovan 2016). They developed an Artificial Neural Network (*ANN*) model using 704 datasets in which they considered *DMR* factor, the number of the wet-dry cycles, Ferric oxide, Silica, and Alumina as five inputs to predict the resilient modulus of stabilized subgrade. The results of this study compared to the *SVR* showed that the *ANN* approach has more accuracy in predicting the resilient modulus. So, the values of  $R^2$  are 0.9857 and 0.9593 for *ANN* and *SVR*, respectively. These amounts for MSE are 49784 and 137870 for *ANN* and *SVR*, respectively.

In a most recent related study, resilient modulus of flexible pavement foundation has been predicted utilizing the extreme gradient boosting based optimized models. In this research four optimization algorithms as *PSO*, *SSO*, *MVO* and *SCA* have been employed for tuning the internal hyper-parameters of the *XGB* model. The results showed that the *PSO* – *XGB* has the highest ability in predicting the resilient modulus of flexible pavement foundation (Sarkhani *et al.* 2022).

Two different regression techniques based on the extreme learning machine have been used by Pal and Deswal (Pal and Deswal 2014) to predict the resilient modulus of subgrade soils. A total of 891 dataset with nine

inputs as Soil particles passing through a #200 sieve, liquid limit, plasticity index, optimum water content, natural water content, saturation degree, unconfined compressive strength, confining pressure, and deviatoric stress have been utilized to predict the resilient modulus of subgrade soil. This database was randomly divided into 594 and 297 data for training and testing data, respectively. The results of both mentioned models demonstrated acceptable accuracy in predicting the resilient modulus.

Sadrossadat *et al.* (2018) utilized linear genetic programming to indirectly predict the resilient modulus of subgrade. Soil particles passing through a #200 sieve, liquid limit, plasticity index, optimum water content, natural water content, saturation degree, unconfined compressive strength, confining pressure, and deviatoric stress were considered as input parameters in different combinations. Finally, considering the amount of  $R^2$  equal to 0.8464, the results of linear genetic programming illustrated an average accuracy in predicting the resilient modulus.

Eventually, in the recent study, Gabr *et al.* (2021) utilized an Extreme Learning Machine using Equilibrium Optimizer to predict the resilient modulus of the recycled concrete aggregate-made subgrade. Fourteen different mix designs using recycled concrete aggregate and various admixtures have led to a total of 224 data to train and test the mentioned model. Recycled concrete aggregate, bulk stress, and amounts of admixtures are taken as input data to estimate the resilient modulus of subgrade. The  $R^2$  of 0.924 demonstrated that the optimized Extreme Learning Machine approach has relatively high accuracy in predicting the resilient modulus of subgrade.

### 1.1 The idea, contribution, and objective

With the advancement of the Artificial Intelligence-based approaches in the field of Civil and Geotechnical engineering, and considering the high accuracy of the predictions using these techniques, their application in predicting resilient modulus and other fields also expanded. So an extremely large number of papers and journals are currently devoted to neural network application; even several articles can be cited from geotechnical journals recently published in the field of geotechnical engineering (Chauhan *et al.* 2022, Duan *et al.* 2022, Jaber 2022, Liu *et al.* 2022, Lv *et al.* 2020, Muneer *et al.* 2022, Samantaray *et al.* 2022, Yan and Chen 2022). There are numerous methods in the data mining, and neural network field, which extreme gradient boosting method is one of them that has recently received a lot of attention in published articles because of its capability in simulation procedures (Dhar *et al.* 2022, Dong *et al.* 2022, Dong *et al.* 2022, Dosdoğru and İpek, 2022, Gumaei *et al.* 2022, Ibrahim *et al.* 2022, Inan and Rahman 2022, Ismail and Islam Mondal 2022, Kaveh *et al.* 2022, Kavzoglu and Teke 2022, W. Lv *et al.* 2022, Ma *et al.* 2022, Smith and Alvarez 2022, Tao *et al.* 2022, Thenmozhi and Helen 2022, Thomas and Vimina 2022, Zeng *et al.* 2022). Therefore, by analyzing the published literature corresponding to the subject of this article, it was determined that an extreme gradient boosting method had

Table 1 Summary of the previous studies on predicting the  $M_R$  of flexible pavement bases

Reference	Year	Inputs	Model	$R^2$	RMSE
(Hanittinan 2007)	2007	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	ANN	0.978	-
(Park <i>et al.</i> 2009)	2009	$\gamma_d$ , $C_u$ , P#200, PI, $\sigma_o$ , $\sigma_d$ , and $\omega_{opt}$	ANN	0.937	-
(Zaman <i>et al.</i> 2010)	2010	$\omega_c$ , $\gamma_d$ , PI, P#200, $q_u$ , $\sigma_d$ , and $\theta$	RBFNN	0.6284	-
(Yan <i>et al.</i> 2014)	2014	$\omega_c$ , $\gamma_d$ , PI, P#200, $q_u$ , $\sigma_d$ , and $\theta$	GEP	0.7815	-
(Pal and Deswal 2014)	2014	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	ELM	0.982	3.47
(Sadrossadat <i>et al.</i> 2016)	2016	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	ANFIS	0.974	4.85
(Chou <i>et al.</i> 2016)	2016	$\gamma_d$ , $C_u$ , P#200, PI, $\sigma_o$ , $\sigma_d$ , and $\omega_{opt}$	SFA – LSSVR	0.9216	14.77
(Sadrossadat <i>et al.</i> 2018)	2018	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	LGP	0.8649	11.91
(Ghorbani <i>et al.</i> 2020)	2020	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	ANN – GA	0.97	5.5
(Kayadelen <i>et al.</i> 2021)	2021	P#200, PI, LL, $\sigma_o$ , $\sigma_d$ , $S_r$ , $\omega_{opt}$ , $\omega_c$ , and $q_u$	RF	0.9801	4.6
(Heidarabadizadeh <i>et al.</i> 2021)	2021	$\gamma_d$ , $C_u$ , P#200, PI, $\sigma_o$ , $\sigma_d$ , and $\omega_{opt}$	SVM – CBO	0.9978	3.1348
(Kayadelen <i>et al.</i> 2021)	2021	$\gamma_d$ , $C_u$ , P#200, PI, $\sigma_o$ , $\sigma_d$ , and $\omega_{opt}$	RF	0.9409	16.85

\*ANFIS = Adaptive Neuro-Fuzzy Inference System, ELM = Extreme Learning Machine, ANN = Artificial Neural Network, GA = Genetic Algorithm, RF = Random Forests, LGP = Linear Genetic Programming, SVM = Support Vector Machine, CBO = Colliding Bodies Optimization, SFA = Smart Firefly Algorithm, LSSVR = Least Square Support Vector Regression, GEP = Genetic Programming, RBFNN = Radial Basis Function Neural Network,  $\gamma_d$  = Dry Density,  $C_u$  = Uniformity Coefficient,  $\theta$  = Bulk Stress

not been developed around this topic. On the other hand, the extreme gradient boosting method was hybridized with several optimization algorithms (Ding *et al.* 2020, Ha *et al.* 2021, Kardani *et al.* 2020, Linh *et al.* 2022, Nguyen *et al.* 2021, Tahsin *et al.* 2021, Tao *et al.* 2021, Zhang *et al.* 2021, Zhou *et al.* 2021, Zhou *et al.* 2021), but there is no published paper using the Black widow optimization integrated with the extreme gradient boosting method, which it developed as an attractive novelty in this paper. Also, in order to raise the comprehensiveness and robustness of the article, it was tried to develop models with different combinations of input variables based on the literature, so-called deep learning, which leads to determining the most important variables in the prediction process. At last, it was attempted to compare the results of the present study with literature to approve the developed extreme gradient boosting method's ability (Ghanizadeh *et al.* 2021, Kaloop *et al.* 2019, Maalouf *et al.* 2012). An outline of the previous studies on predicting the  $M_R$  of flexible pavement foundations is summarized in Table 1.

The present study aims to assess and design two novel deep learning-based hybrid intelligence approaches, PSO-XGB and BWOA-XGB, by optimizing the XGB through PSO and BWOA to predict the resilient modulus of subgrade soil. The prediction process was divided into two sections. In the first section, the models were developed by different combinations of input variables based on the literature entitled deep learning, and the second section scrutinized the most appropriate model deeply. For the deep learning in the  $M_R$  estimation process, different models were constructed based on various combinations of input variables ( $M1 - M4$ ), consists of the number of W-D cycles (WDC), the ratio of free lime to SAF (CSAFR), the ratio of maximum dry density to the optimum moisture content (DMR), confining pressure ( $\sigma_3$ ), and deviatoric stress ( $\sigma_d$ ). Two XGB structures were created for the estimation goals.

To receive the greatly precise models, determinative

variables of this method were optimized using different metaheuristic methods named particle swarm optimization (PSO) and black widow optimization algorithm (BWOA). The accuracy of the developed models was assessed and compared with literature proposed with GPR, SVM, and PSO-ELM approaches (Ghanizadeh *et al.* 2021, Kaloop *et al.* 2019, Maalouf *et al.* 2012).

## 2. Methodology

### 2.1 Dataset explanation

In order to expand the proposed models to predict the resilient modulus of subgrade soil, a total of 704 experimental dataset were prepared from published peer-reviewed papers (Khouri 2005). Various data set ratios in between these sub-groups were used (Hammerstrom 1993, Looney 1996, Stone 1974). Resilient modulus can be determined using various parameters, which can be considered as input parameters in data mining-based studies. In this study, WDC, CSAFR, DMR,  $\sigma_3$  and  $\sigma_d$  are taken as input parameters for predicting the resilient modulus of subgrade soil. Statistical parameters of input and output datasets for training and testing data are distributed to 75% and 25%, respectively, as shown in Table 2. The correlation between different pair parameters can be calculated using the Pearson correlation coefficient (Eq. (2)).

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \quad (2)$$

in which,  $cov(X,Y)$  illustrates the covariance for  $Y$  and  $X$  variables. Also,  $\sigma_X$  and  $\sigma_Y$  demonstrate the standard deviation of  $Y$  and  $X$ . Fig. 1 presents the visualized form of the Pearson correlation coefficient of various input and output parameters using a correlation matrix. Large positive

Table 2 The statistical description of input and output variables

Model variables and datasets	Statistical parameters							
	Min.	Max.	St. D.	Skew.	Range	Kurt.	Avg.	Med.
<b>Inputs:</b>								
<i>WDC</i>								
Training data	0	30	10.95	0.442	30	-1.1031	12.871	8
Testing data	0	30	11.732	0.4495	30	-1.295	12.568	8
<i>CSAFR</i>								
Training data	0.113	0.51	0.1837	0.6407	0.397	-1.5874	0.2578	0.13
Testing data	0.113	0.51	0.1788	0.8045	0.397	-1.35	0.2448	0.13
<i>DMR (kN/m<sup>3</sup>)</i>								
Training data	2.34	4.63	0.7006	0.37	2.29	-0.9193	3.274	3.37
Testing data	2.34	4.63	0.7423	0.3904	2.29	-1.131	3.242	3.37
$\sigma_3$ (kPa)								
Training data	0	138	49.0417	-0.0445	138	-1.3206	70.5682	69
Testing data	0	138	48.1622	0.0226	138	-1.2492	68.804	69
$\sigma_d$ (kPa)								
Training data	69	277	77.615	0.0524	208	-1.367	169.195	138
Testing data	69	277	76.949	-0.0817	208	-1.351	179.687	208
<b>Output:</b>								
<i>M<sub>R</sub></i> (MPa)								
Training data	603	9803	1825.371	1.1694	9200	1.7701	3661.178	3427
Testing data	585	9591	1955.47	0.997	9006	0.79112	3752.7	3507.5

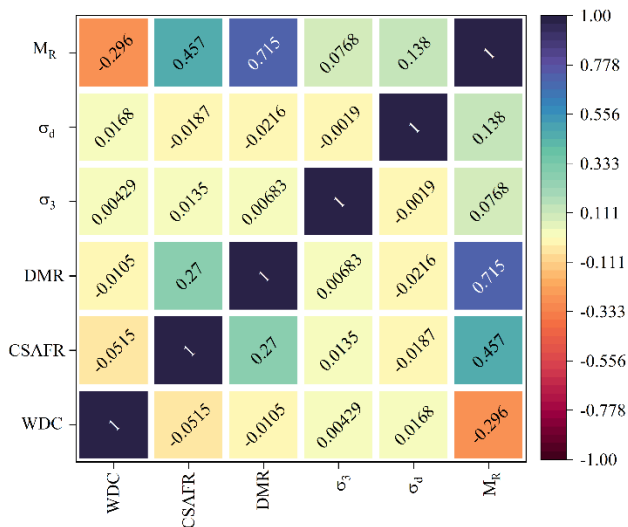


Fig. 1 The correlation matrix between variables

or negative amounts of the matrix components may lead to difficulty and divergence interpreting the expository effects of the parameters on the model response. It should be considered that large amounts of the Pearson correlation coefficients between input and output are not critical, considering this fact, despite relatively large amounts of Pearson matrix (Fig. 1) due to correlating between input and output variables, this doesn't lead to divergence of the model. However, it should be reported that resilient modulus has a middle-high correlation factor with CSAFR and DMR, equal to 0.457 and 0.715, respectively.

Fig. 2 shows three-dimensional surface plots of the datasets gained by interpolation using a thin-plate spline. As it can be observed, the relation between  $M_R$  and the input parameters are extraordinarily non-linear and complicated. For instance, in Fig. 2(a), the  $M_R$  tends to be high for large amounts of  $\sigma_d$  and DMR values at 250 kPa and 4.5, respectively. But as can be seen from Figs. 2(b, c),  $M_R$  does not have a distinct and regular relationship with DMR and WDC. Therefore, expanding an AI-based model seems necessary for predicting different values of  $M_R$  using the introduced input parameters.

## 2.2 Utilized prediction methods

### 2.2.1 Extreme gradient boosting method

The core of extreme gradient boosting is one of the hybrid approaches considering the gradient boosting tree (Chen *et al.* 2015). Gradient boosting is a representative approach to boosting through the ensemble technique. One of the gradient boosting-based algorithms is extreme gradient boosting, which has highly efficient performance.

The extreme gradient boosting approach is usually admired because of its excellent efficiency in manufacturing and Kaggle machine learning competitions. Extreme gradient boosting is a similar approach to the decision tree of gradient boosting, that is in accordance with the clustering and regression tree approach (Ding *et al.* 2020, Le *et al.* 2019, Zhang *et al.* 2021, Zhou *et al.* 2019, Zhou *et al.* 2019). It can create multiple faint assessors on the data-sets and then brief the modeling results of the faint

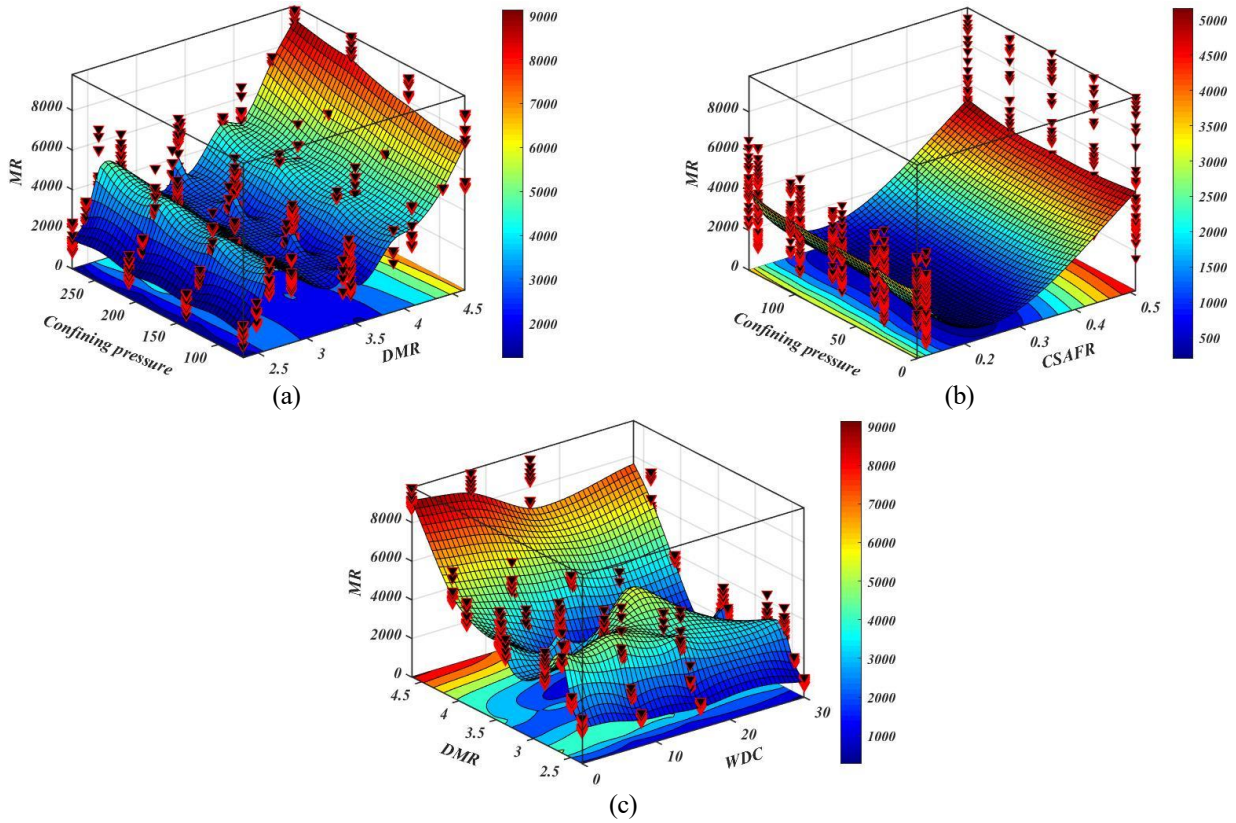


Fig. 2 Surface plots of  $M_R$  versus input variables

assessors. Equivalently, the extreme gradient boosting approach can effectively operate using clustering and regression problems to achieve superior performance than that of the single (Zhou *et al.* 2019). Indeed, it is capable of representing a soft computing library that combines a new approach with the decision tree-based gradient boosting algorithm.

The optimized extreme gradient boosting object function reduced the expression that adjusted it to prevent overfitting (Chen and Guestrin 2016); hence the object function was created by two segments. The prime part is employed to assess the difference between the predicted and measured amounts, and the second part is related to the adjusting step. The variant and deviation of the predicted values determine the model accuracy. A classification of datasets is  $D = \{(x_i, y_i)\}$  consists of  $m$  specifications and  $n$  specimens and the predictor is a surplus pattern comprised of  $k$  basis approaches. The results of example forecasting may be illustrated as bellows

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in \varphi \quad (3)$$

$$\varphi = \{f(x) = w_s(x)\} (s: R^m \rightarrow T, w_s \in R^T) \quad (4)$$

$x_i$  : One of the samples

$f_k(x_i)$  : Prediction score for a given sample

$\varphi$  : The set of regression trees

$s$  : Structural parameters

$w$  : Leaf weight

$T$  : The number of leaves in the tree

$K$  : The number of trees

$\hat{y}_i$  : The predicted label

The extreme gradient boosting approach represents the complexity of the model to assess the model accuracy in order to optimize the ensemble tree and obtain the best efficiency. Accordingly, the object efficiency comprises the conventional waste performance and the model complexity.

$$Obj^{(t)} = \sum_{i=1}^m l(y_i^t, \hat{y}_i^{(t-1)} + f_t(x_i)) + \sum_{k=1}^t \Omega(f_k) \quad (5)$$

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \quad (6)$$

where  $i$  and  $m$  illustrate the issue of specimens in the dataset and the entire amounts of the data presented in the  $k$ th tree, respectively. The first phrase of Eq. (5) illustrates the conventional waste subordinate, computing the differences between the measured and predicted values. Another phrase in Eq (5) demonstrates the complexity of the approach. Besides,  $\gamma$  and  $\lambda$  parameters exhibit the properties that are

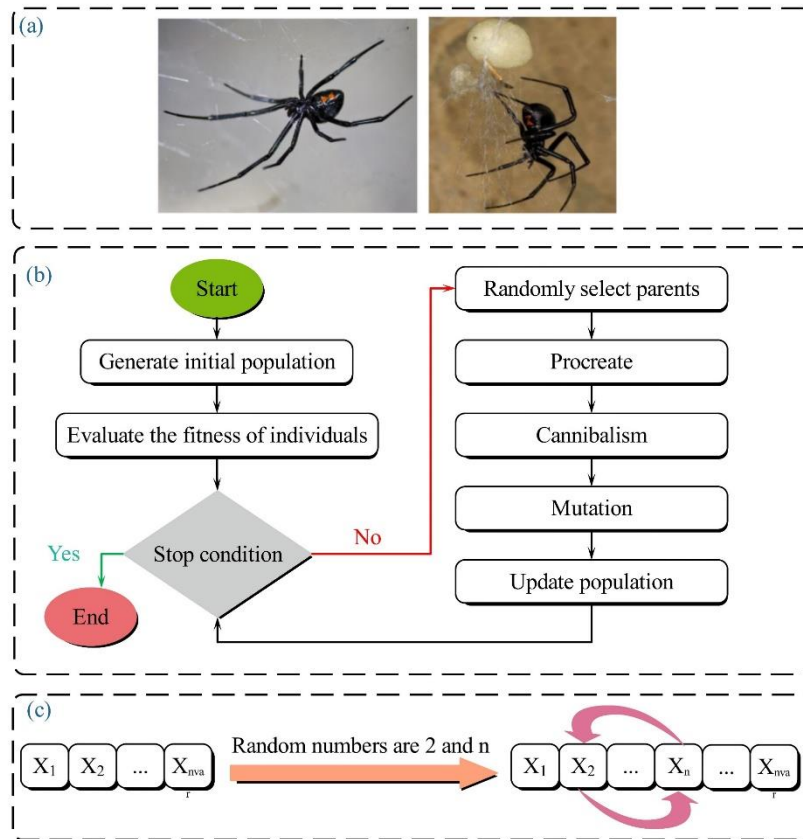


Fig. 3 (a) Black widow spider (left picture), Put the eggs in the bag (right picture), (b) BWOA flowchart and (c) Mutual mutations in BWOA

assists to stay away from overfitting by clearing the ultimate weights. Subsequently, Taylor expansion has been employed to achieve further simplification of the object subordinate.

$$Obj^{(t)} = \sum_{i=1}^m [f_t(x_i)g_i + \frac{1}{2}(f_t(x_i))^2 h_i] + \gamma T + 0.5\lambda \sum_{j=1}^T w_j^2 \quad (7)$$

where  $g_i$  represents the first derivative obtained on the loss efficiency and  $h_i$  second derivative procured on the loss efficiency.

### 2.2.2 The black widow optimization algorithm (BWOA)

Spiders could be propounded as a kind of insect which has a broad diversity compared with other animals (Hayyolalam and Kazem 2020, Sentenská *et al.* 2020). On the plains, deserts, mountains, and farms, you may encounter black widow spiders beneath the rocks and soil. Investigations demonstrate that the toxicant of a BWO is more deadly compared to the rattlesnake. Female BWOs habit single, however when they coupled, could approximate each other as well as intercross (Sentenská *et al.* 2020). The male ones, that are smaller compared to the female or widow one, are consumed by the female after intercrossing. This treatment could be owing to the objectivity that the female species gets hungry after gestation. Another opinion is that by consuming the male with female, the genes of the father are passed on to the

child. A BWO and its bag for spawning are illustrated in Fig. 3(a) (Hayyolalam and Kazem 2020). The BWOA has been developed by the treatment of this type of spider in generate and anthropophagy. In the present method, there are significant steps like generation, species eating (anthropophagy), and metamorphosis. The flow diagram displays some of the basic phases in the present algorithm. In the black widow spider optimization algorithm, an accidental primary crowd is developed in the first step, and each component is assessed by the target function to specify its compatibility.

In the BWOA, a numerator at every repetition exists that specifies how many times the algorithm is iterated, and one module is surcharged to the counter each time. In the subsequent phase, three phases of generation, anthropophagy, and transformation are conducted on the components of the crowd, then the situation of every solution is recovered in the BWOA. In the ultimate repetition, the highest optimized answer is obtained as the answer to the issue. In the BWOA, each answer of the issue is noticed to be a black spider in accordance with Eq. (8) and has subsequent  $N_{var}$ . In the prime phase,  $n_{Pop}$  responses initially developed an accidentally in the optimization issue space at the beginning (Hayyolalam and Kazem 2020).

$$Widow = [x_1, x_2, x_3, \dots, x_{Nvar}] \quad (8)$$

In the present algorithm, multiple eggs are generated at each phase, and only a few of them remain that are more qualified, and the rest are eliminated. Presume there are two parents, alike  $x_1$  and  $x_2$ , that possess intercourse and generate two new responses, like  $y_1$  and  $y_2$  that are developed in accordance with Eq. (9) and (10), respectively (Fig. 3(b)).

$$y_1 = \alpha x_1 + (1 - \alpha)x_2 \quad (9)$$

$$y_2 = \alpha x_2 + (1 - \alpha)x_1 \quad (10)$$

In the present algorithm, the anthropophagy step is conducted in three approaches. First, the male species is omitted by the female, which is more convenient; afterward, the species is drunk among the children, and the weak components are removed. In the next step, anthropophagy, responses that are more qualified by the parent will lead the parent to feed and destroy that. In the case of transformation, it is presumed that some spiders have changed some of the qualifications of their parents, and here transformations similar to Fig. 3(c) are utilized (Hayyolalam and Kazem 2020)

### 2.2.3 Particle swarm optimization algorithm

PSO is a computational technique that optimizes a particular issue utilizing frequent rectifying nominate solutions, here called particles (Babbar *et al.* 2020, Kennedy and Eberhart 1995) (Fig. 4). Every location vector of a particle is presented by  $X_i^k$ , speed vector by  $V_i^k$ , and fitness value, where  $i$  and  $k$  are the available production and the  $i_{th}$  particle. Within the exploration area, referred particles travel forward to global premier locations based on the premier position and local speed. Here, the smallest value of fitness determines the proper position (Chen *et al.* 2020). Eqs. (11) and (12) update speed of every particle.

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 P_i^k - X_i^k + c_2 r_2 P_g^k - X_i^k \quad (11)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (12)$$

$c_1$  and  $c_2$  : Acceleration coefficients

$\omega$  : Inertia weight (equal to 1)

$r_1$  and  $r_2$  : Random numbers [0, 1]

$P_i$  : The current best location of  $i_{th}$  particles

$P_g$  : The global best among all particles

The lowest and highest value of  $V_i^k$  are -1 and 1, respectively. Here, in this method, three parameters of  $\omega$ ,  $c_1$  and  $c_2$  need to be modified, as their values impact the isotopy speed. For that, to raise this optimization efficiency by variable parameters, a different instance of choosing PSO parameters can be found in the literature (Elsheikh *et al.* 2021, Khoshaim *et al.* 2021).

### 2.2.4 The overall analysis processes

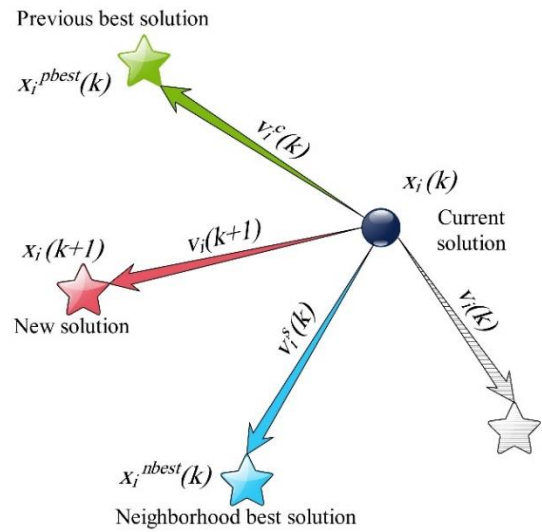


Fig. 4 Process of the particle swarm optimization

The supplied Fig. 5 depicts the whole analysis and modeling outline accomplished in this article. According to this figure, the outline of modeling is principally divided into five stages: (a) dataset gathering; (b) data explanation; (c) models' establishment; (d) models' endorsement and evaluation; (e) outcomes analysis. Two hybridized *XGB* networks (*PSO - XGB* and *BWOA - XGB*) were constructed for estimating the  $M_R$  of modified base materials subject to wet-dry cycles.

### 2.3 Model performance evaluation indices

Qualification and assessment of the proposed networks are the main stages for the model creating procedure. Following the models' creation, it is obligatory to identify the most accurate model for design purposes. For this aim, six widely-used criteria were calculated for assessing the performance and precision of the models, named root mean square error (*RMSE*), the variance accounted factor (*VAF*), coefficient of determination ( $R^2$ ), mean absolute error (*MAE*), and  $A_{10-index}$ . Between the indices as mentioned earlier, the smaller value of *MAE*, *PI* and *RMSE* is proper, and the larger value of *VAF* and  $R^2$  is more reliable. It is valuable to introduce the novel index called  $A_{10-index}$ , in which the value equal to 1.0 depicts an ideal estimation model. The formulation of these indices is

$$R^2 = \left( \frac{\sum_{q=1}^Q (x_q - \bar{x})(z_q - \bar{z})}{\sqrt{[\sum_{q=1}^Q (x_q - \bar{x})^2][\sum_{q=1}^Q (z_q - \bar{z})^2]}} \right)^2 \quad (13)$$

$$RMSE = \sqrt{\frac{1}{Q} \sum_{q=1}^Q (z_q - x_p)^2} \quad (14)$$

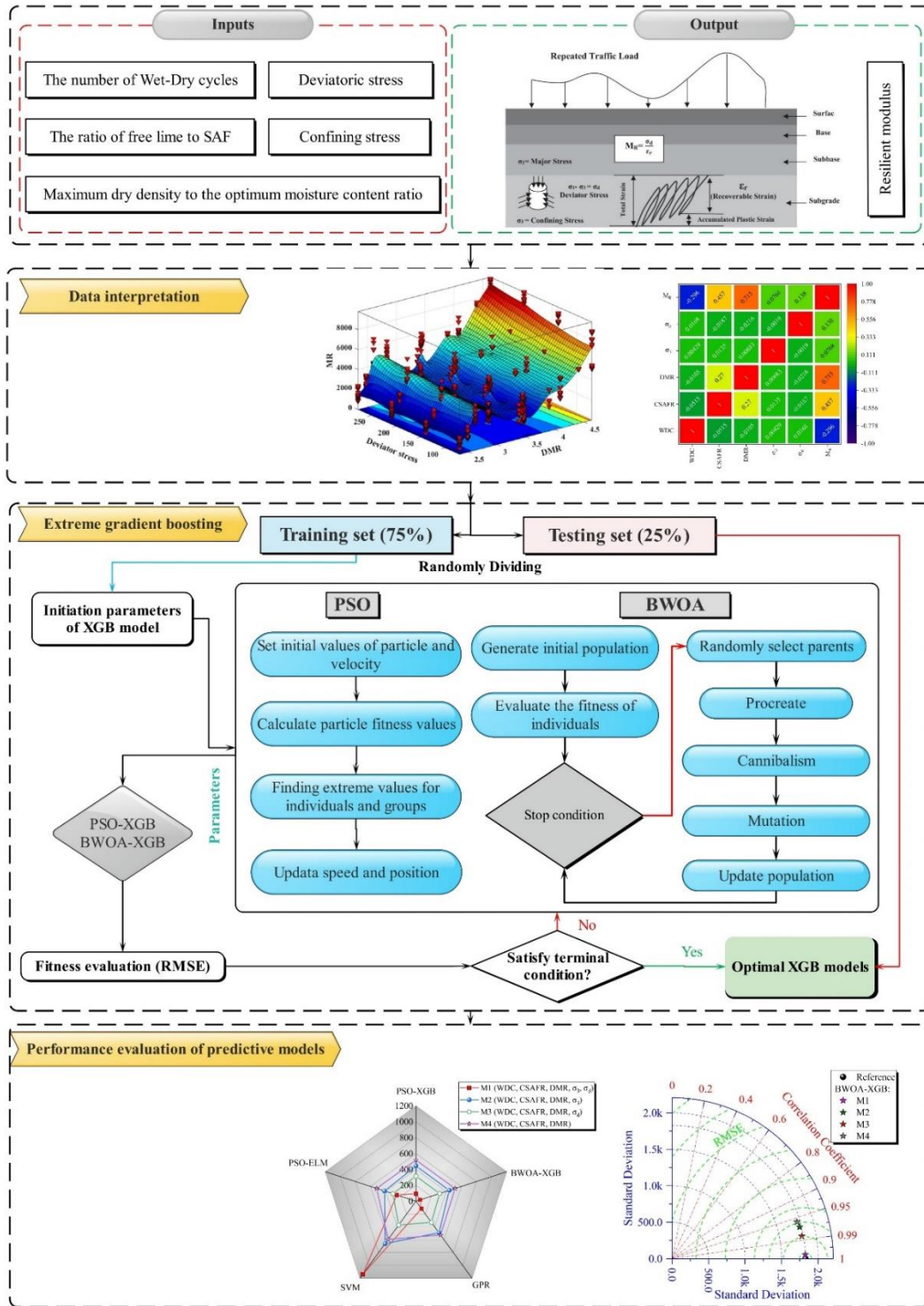


Fig. 5 The overall analysis process of intelligence models

$$MAE = \frac{1}{Q} \sum_{q=1}^Q |z_q - x_q| \quad (15)$$

$$PI = \frac{1}{|\bar{t}|} \frac{RMSE}{\sqrt{R^2 + 1}} \quad (17)$$

$$VAF = \left( 1 - \frac{var(x_q - z_q)}{var(x_q)} \right) * 100 \quad (16)$$

$$A_{10-index} = \frac{n_{10}}{N} \quad (18)$$

- $z_q$  : Estimated values
- $x_q$  : Observed values
- $\bar{t}$  : Average of estimated values
- $\bar{y}$  : Average of observed values
- $N$  : Specimen number
- $n_{10}$  : The number of specimens with a value of observed per estimated between 0.9 and 1.1.

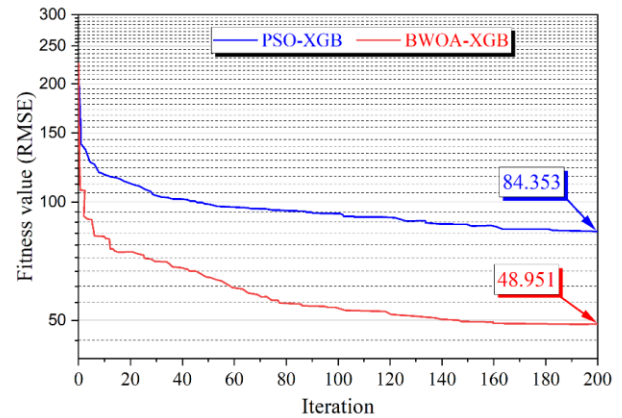


Fig. 6 The fitness reduction in the optimization process

### 3. Results and discussion

The establishment of the *XGB* structures was accomplished according to the outline in Fig. 5. For the first stage, the initialization activity of the *XGB* networks' main terms were performed. After that, the principal variables of considered optimization algorithms (*PSO*, and *BWOA*) were regulated as provided in Table 3. The primary purpose was to develop a hybrid network, where mentioned metaheuristic algorithms were considered to optimize the principal parameters of the *XGB* models as presented in Table 3. At last, two hybridized *XGB* structures were proposed, followed by training and validating.

The convergence figures of the fitness index (*RMSE*) for the case of developed hybrid *XGB* networks are scrutinized as Fig. 6. It is understandable from convergence figures that the *BWOA – XGB* network is declining in the process of optimization, in which the lowest *RMSE* was reached at the smallest iteration in comparison with *PSO – XGB* model. As it is clear, *BWOA – XGB* network could be reached the smallest fitness value at 48.951MPa, almost in half compared to *PSO – XGB* (*RMSE* = 84.353MPa). Therefore, the proper model by evaluating the *RMSE* and decline speed results in the largest  $R^2$  is for *BWOA* algorithm.

#### 3.1 Comparison analysis of the developed model

The results of the hybridized *XGB* models for estimating the resilient modulus of modified base materials subject to wet-dry cycles are provided and explored as follows. The prediction process was divided into two sections. In the first section, the models were developed by different input variables based on the literature so-called deep learning, and the second section scrutinized the most appropriate model deeply. This part describes the results of the first section was aimed at deep learning. For the deep learning in the  $M_R$  estimation process, different models were constructed based on various combinations of input variables ( $M1 – M4$ ). The first model ( $M1$ ) contains all inputs named *WDC*, *CSAFR*, *DMR*,  $\sigma_3$ , and  $\sigma_d$ . The  $M2$  model includes *WDC*, *CSAFR*, *DMR*, and  $\sigma_3$ . The third model contains the *WDC*, *CSAFR*, *DMR*, and  $\sigma_d$  by

deleting  $\sigma_3$ . And the last model ( $M4$ ) just has *WDC*, *CSAFR*, and *DMR* as input variables. These combinations of the inputs were selected based on the published articles (Ghanizadeh *et al.* 2021, Kaloop *et al.* 2019, Maalouf *et al.* 2012) in order to have a comprehensive comparison as well as accuracy proof. As presented earlier, two *XGB* structures were created for the estimation goals. To receive the greatly precise models, determinative variables of this method that play an essential role during the learning process were optimized using different metaheuristic methods named *PSO* and *BWOA*. The collected field data information was separated into train and test dataset randomly by the percent of 75 and 25%. The comparison of this study with literature considering the results of deep learning provided in Table 4 for  $M1 – M4$  models, as well as the radar figures (Fig. 7) for the values of  $R^2$  and *RMSE*. As it is clear from this table, the highest accuracy of this study, developed GPR (Ghanizadeh *et al.* 2021) and *PSO-ELM* (Kaloop *et al.* 2019) belonged to the  $M1$  with input variables of *WDC*, *CSAFR*, *DMR*,  $\sigma_3$ , and  $\sigma_d$ , with an exception of *SVM* (Maalouf *et al.* 2012). The  $R^2$  and *RMSE* values of *PSO-XGB* and *BWOA-XGB* proposed from this study are equal to 0.9973 and 94.16 MPa, and 0.9991 and 55.19 MPa, respectively. The highest  $R^2$  and the lowest *RMSE* values for GPR (Ghanizadeh *et al.* 2021) and *PSO-ELM* (Kaloop *et al.* 2019) were for  $M1$  model at 0.995 and 116.94 MPa, and 0.981 and 253.44 MPa, respectively. In contrast, the weakest input combination for *SVM* (Maalouf *et al.* 2012) model was  $M1$ , with  $R^2$  at 0.64. However, the *SVM* (Maalouf *et al.* 2012) was proposed the  $M3$  model as the best model in contrast with other models. On the other hand, the worst combination for predicting the  $M_R$  is as  $M4$  model with *WDC*, *CSAFR*, and *DMR* as reported by GPR (Ghanizadeh *et al.* 2021), *PSO-ELM* (Kaloop *et al.* 2019), *PSO-XGB* and *BWOA-XGB*, with the  $R^2$  at about 0.92 and *RMSE* at roughly 520 MPa. All in all, according the results description and Table 4, best model with combination of *WDC*, *CSAFR*, *DMR*,  $\sigma_3$ , and  $\sigma_d$  is recognized as the most suitable model, and because of this result, second section of this study was aimed to scrutinize the results of the  $M1$  model.

Table 3 The algorithms' parameters and models' optimal parameters

Method	Parameters	Value	Optimal parameter	Value
PSO	Cognitive coefficient 1 ( $C1$ )	1	$num\_boosting\_rounds$	75
	Cognitive coefficient 2 ( $C2$ )	2	$\xi$	0.218
	Maximum velocity ( $V_{max}$ )	5	$\lambda$	0.34
	Maximum inertia weight ( $W_{max}$ )	0.99		
	Minimum inertia weight ( $W_{min}$ )	0.2		
	Training population	250		
	Training iteration	200		
BWOA	Procreating rate ( $PR$ )	0.8	$num\_boosting\_rounds$	89
	Cannibalism rate ( $CR$ )	0.5	$\xi$	0.185
	Mutation rate ( $PM$ )	0.4	$\lambda$	0.75
	Training population	250		
	Training iteration	200		

Table 4 Comparison of the developed models considering different input combinations

Model	Inputs	Index	Models				
			PSO-XGB	BWOA-XGB	GPR (Ghanizadeh <i>et al.</i> 2021)	SVM (Maalouf <i>et al.</i> 2012)	PSO-ELM (Kaloop <i>et al.</i> 2019)
M1	WDC, CSAFR, DMR, $\sigma_3, \sigma_d$	$R^2$	0.9973	<b>0.9991</b>	0.995	0.64	0.981
		$RMSE$	94.16	<b>55.199</b>	116.94	1134.592	253.439
M2	WDC, CSAFR, DMR, $\sigma_3$	$R^2$	0.9413	0.9419	0.931	0.875	0.948
		$RMSE$	443.697	441.47	491.145	659.75	415.554
M3	WDC, CSAFR, DMR, $\sigma_d$	$R^2$	0.9701	0.9705	0.968	0.959	0.973
		$RMSE$	315.73	313.759	329.743	371.309	304.451
M4	WDC, CSAFR, DMR	$R^2$	0.9201	0.9203	0.920	0.90	0.921
		$RMSE$	517.535	516.778	525.932	593.54	521.08

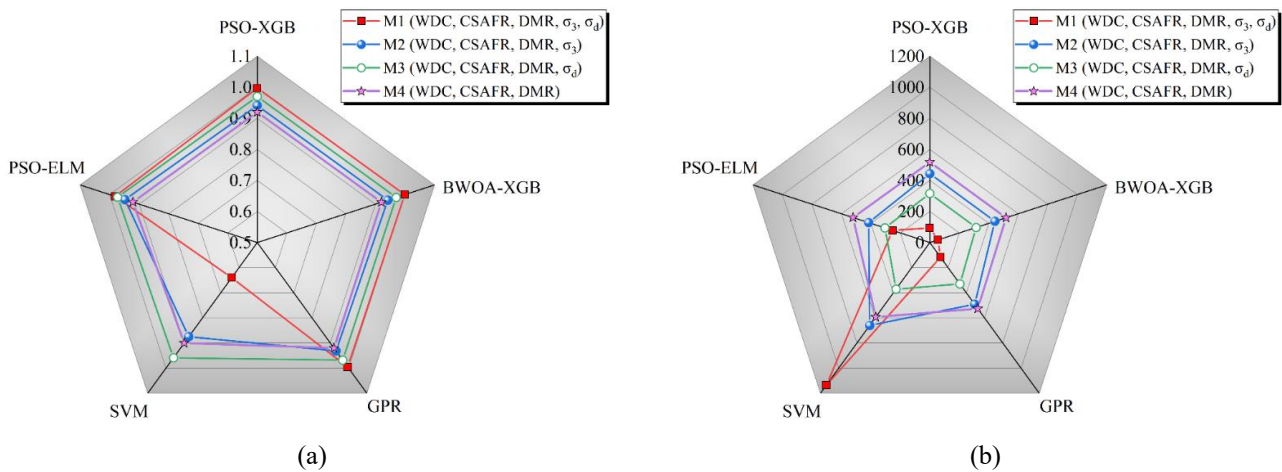


Fig. 7 Radar plots of results; (a)  $R^2$  and (b)  $RMSE$

Another diagram that can be provided in order to assess the efficiency of the models comprehensively is the Taylor diagram (Fig. 8). This diagram provides the values of correlation coefficient ( $R$ ),  $RMSE$  and Standard deviation in a figure altogether. In this diagram, the horizontal and

vertical axes depict the Standard deviation, the green curves show the values of  $RMSE$ , and the red radial lines are the  $R$ . The dark mark with the solid circle is recognized as the reference point adapted from observations with  $RMSE$  equals zero, the highest  $R$  and a computed standard

Table 5 Comparison of the developed models with literature

Data category	Inputs	Index	Models				
			PSO-XGB	BWOA-XGB	GPR (Ghanizadeh <i>et al.</i> 2021)	SVM (Maalouf <i>et al.</i> 2012)	PSO-ELM (Kaloop <i>et al.</i> 2019)
Train	WDC, CSAFR, DMR, $\sigma_3$ , $\sigma_d$	$R^2$	0.9973	0.9991	0.995	0.64	0.981
		$RMSE$	94.1601	55.1988	116.94	1134.592	253.439
		$MAE$	53.572	28.0841			
		$PI$	0.0129	0.0075			
		$VAF$	99.734	99.9086			
		$A_{10-Index}$	0.9886	0.9981			
Test	WDC, CSAFR, DMR, $\sigma_3$ , $\sigma_d$	$R^2$	0.9986	0.9995			
		$RMSE$	74.5452	42.7026			
		$MAE$	49.6989	24.3213			
		$PI$	0.0099	0.0057			
		$VAF$	99.8551	99.9524			
		$A_{10-Index}$	0.983	0.9943			

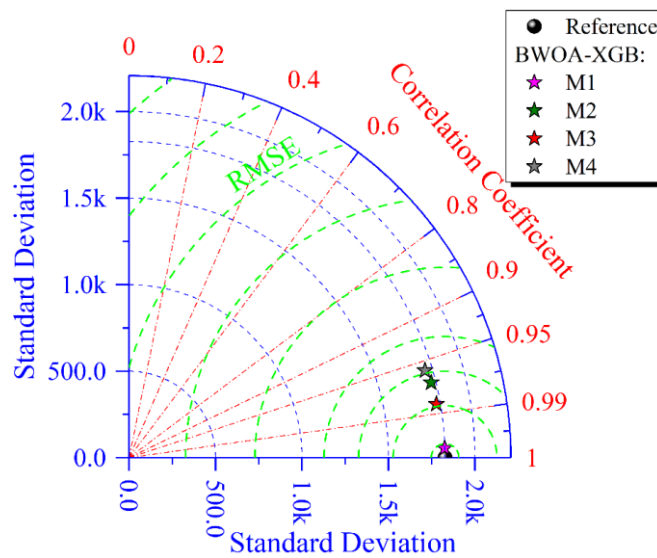


Fig. 8 Taylor diagram of the BWOA-XGB models

deviation. This diagram was plotted for the proposed hybrid BWOA-XGB model for the results of deep learning. It is observed that the  $M1$  model has been capable of possessing a closer location to the reference point compared to other input combinations ( $M2 - M4$ ).

Moreover, in the second section, the results of the model  $M1$  were evaluated deeply by considering other important criteria such as  $MAE$ ,  $PI$ ,  $VAF$ , and  $A_{10-Index}$  along with the  $R^2$  and  $RMSE$  for the training and testing dataset. The results of the created structures, along with the published literature, have been provided and gathered in Table 5 and Figs. 9 and 10. As can be gained from Table 5, both developed  $XGB$  models could outperform literature (Ghanizadeh *et al.* 2021, Kaloop *et al.* 2019, Maalouf *et al.* 2012), with  $R^2$  equal to at least 0.9973 higher than PSO-ELM (Kaloop *et al.* 2019), SVM (Maalouf *et al.* 2012), and GPR (Ghanizadeh *et al.* 2021). Interestingly, the lowest value of  $RMSE$  was for GPR (Ghanizadeh *et al.* 2021) at

116.94 MPa before this study, while this study could gain the extremely lower  $RMSE$  owned by BWOA-XGB model at 55.198 MPa, almost lower than a half. Also, between the proposed models by the present study, the PSO-XGB model was slightly weaker than another model in both train and test phase, but still capable than literature. The explanations indicate the BWO algorithm's capability in the determining the optimal value of  $XGB$  determinative parameters in  $M_R$  prediction procedure. The provided Figs. 9 and 10 depict the results of the models by plotting the correlation figures and error percentage distribution of  $M_R$ . The Figs. 9 and 10 (a) show the remarkable correlation between measured and estimated  $M_R$  for PSO-XGB and BWOA-XGB, respectively. Also, Figs. 9 and 10(c) specify that the higher distribution of errors about zero line, the higher accuracy. Therefore, the developed BWOA-XGB network results in a higher number of cases around zero; additionally, it depicts that this model has proper error distribution, where is limited in the interval of  $\pm 15\%$ .

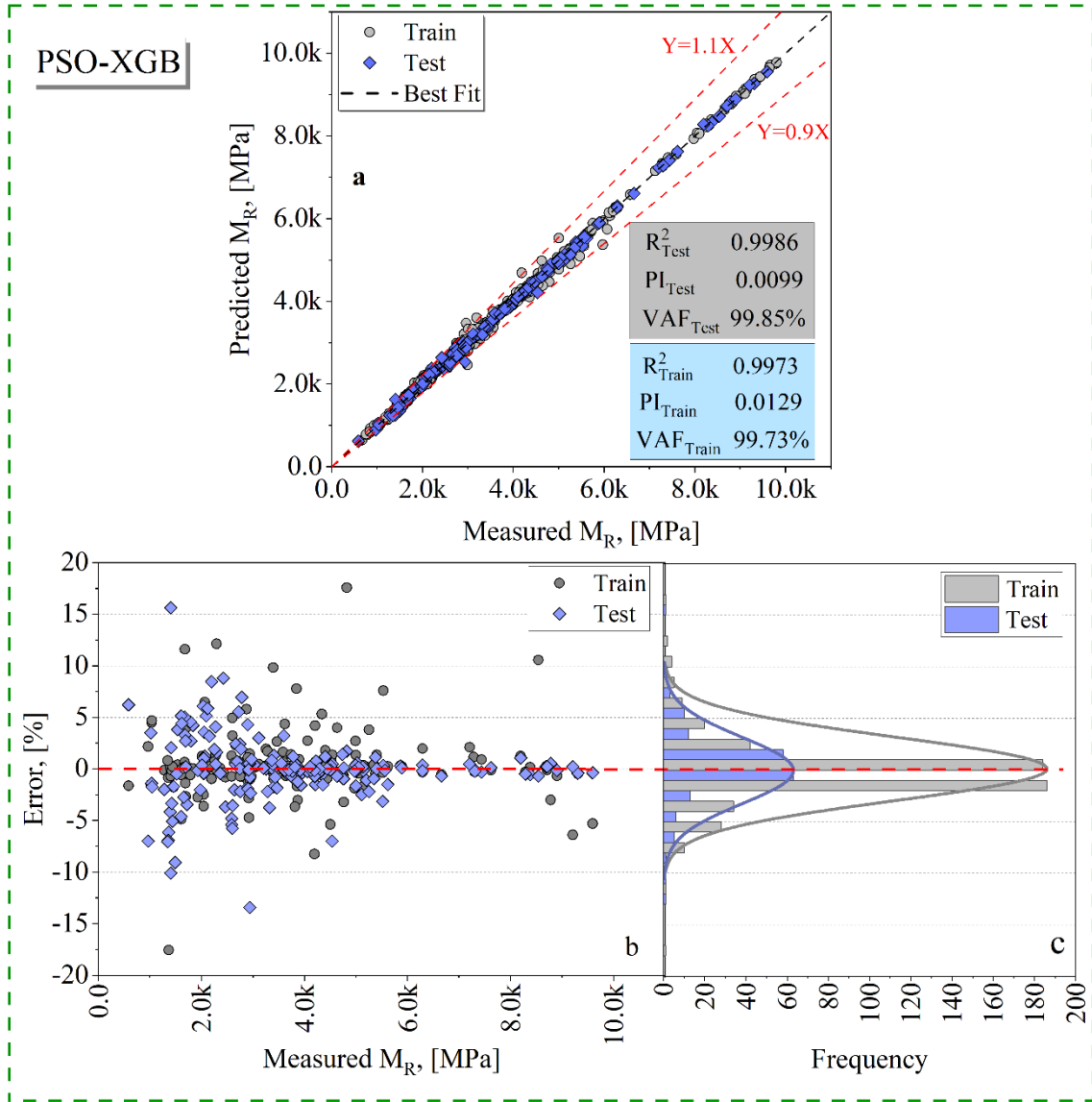


Fig. 9 The results of PSO-XGB for M1

Fig. 11 illustrates the amounts of  $U_{95}$  which are familiar as the performance evaluators, in which the lower the amounts of uncertainty present the higher the generalization performance. It can be concluded that the M1 model contains the least uncertainty in comparison with other models, with 118.4812 and 153.0713 for the testing and training dataset, respectively. This represents the greater generalization capability of the M1 model compared to other approaches. The second rank belongs to the M3 model considering the  $U_{95}$  values, followed by M2 and M4 models.

**4. Conclusions**

The present article proposed a novel hybridized extreme gradient boosting model for estimating the resilient modulus ( $M_R$ ) of modified base materials subject to wet-dry cycles. The prediction process was divided into two

sections. In the first section, the models were developed by different combinations of input variables based on the literature entitled deep learning, and the second section was scrutinized the most appropriate model deeply. For the deep learning in the  $M_R$  estimation process, different models were constructed based on various combinations of input variables (M1 – M4), consists of the number of W-D cycles (WDC), the ratio of free lime to SAF (CSAFR), the ratio of maximum dry density to the optimum moisture content (DMR), confining pressure ( $\sigma_3$ ), and deviatoric stress ( $\sigma_d$ ). Two XGB structures were created for the estimation goals. To receive the greatly precise models, determinative variables of this method were optimized using different metaheuristic methods named particle swarm optimization (PSO) and black widow optimization algorithm (BWOA). It should be mention that the models of this study have been developed using some limit data so, the results are specific and cannot be generalized to all soils.

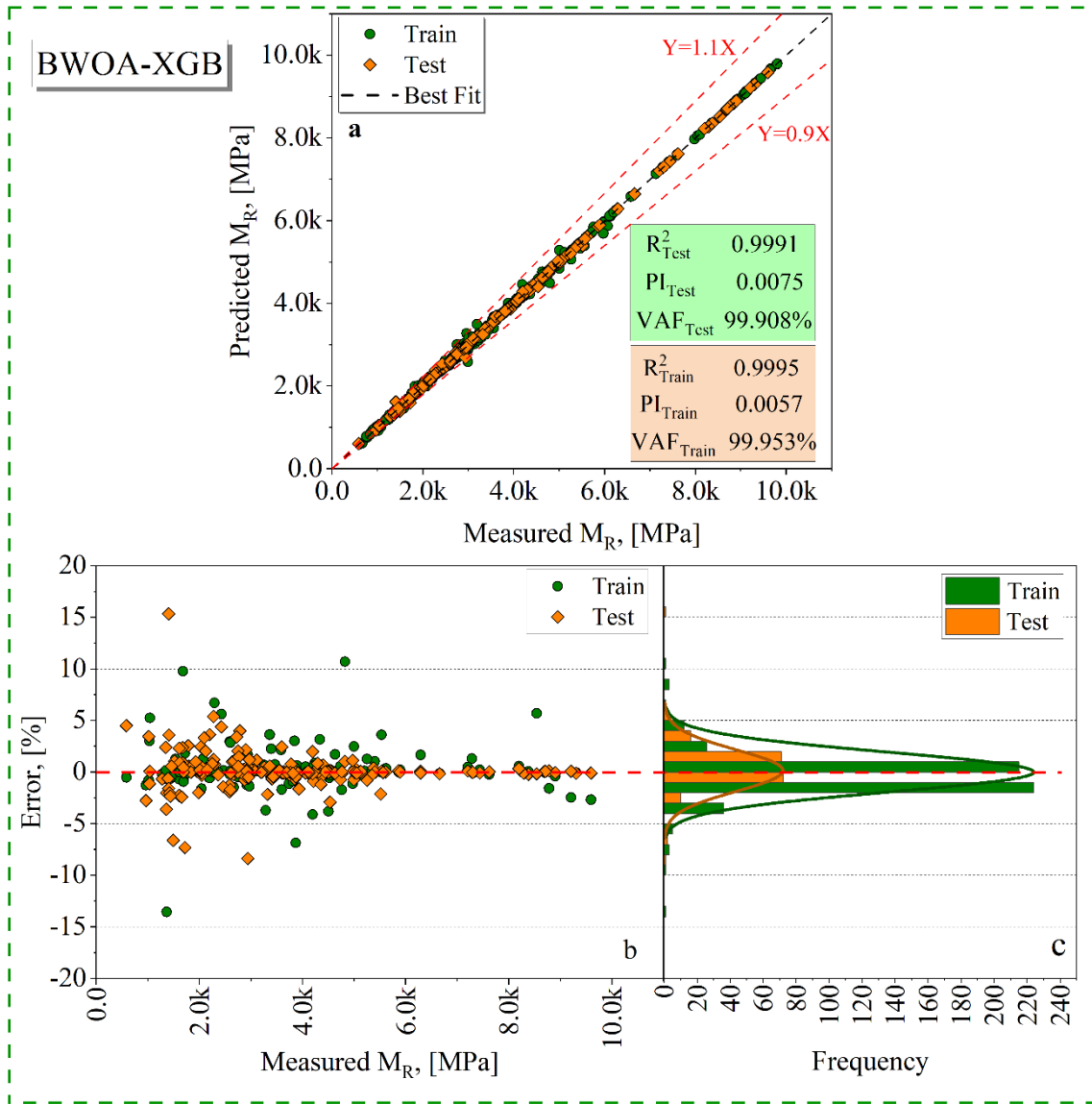


Fig. 10 The results of BWOA-XGB for M1

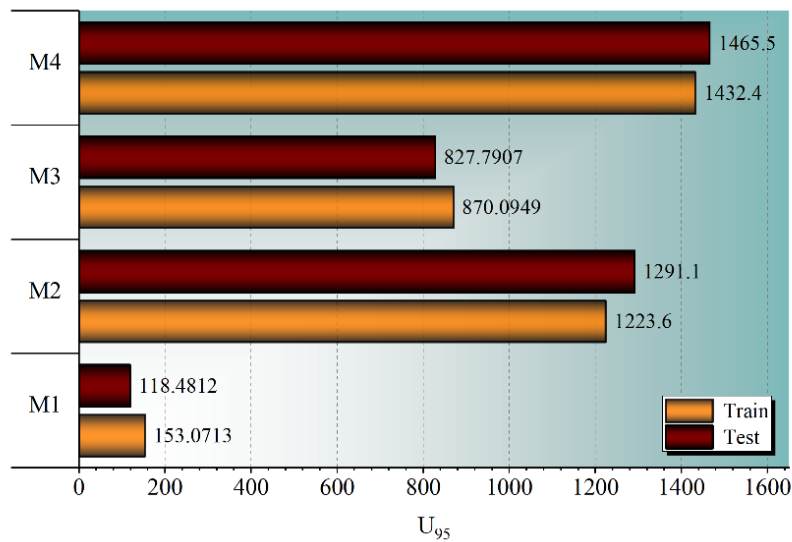


Fig. 11 The  $U_{95}$  test values of referred models

- As it was clear the highest accuracy of this study, developed GPR (Ghanizadeh *et al.* 2021) and PSO-ELM (Kaloop *et al.* 2019) belonged to the *M1* with input variables of *WDC*, *CSAFR*, *DMR*,  $\sigma_3$ , and  $\sigma_d$ . The  $R^2$  and *RMSE* values of PSO-XGB and BWOA-XGB proposed from this study are equal to 0.9973 and 94.16 MPa, and 0.9991 and 55.19 MPa, respectively. The highest  $R^2$  and the lowest *RMSE* values for GPR (Ghanizadeh *et al.* 2021) and PSO-ELM (Kaloop *et al.* 2019) were for *M1* model at 0.995 and 116.94 MPa, and 0.981 and 253.44 MPa, respectively.
- On the other hand, the worst combination for predicting the  $M_R$  is as *M4* model with *WDC*, *CSAFR*, and *DMR* as reported by GPR (Ghanizadeh *et al.* 2021), PSO-ELM (Kaloop *et al.* 2019), PSO-XGB and BWOA-XGB, with the  $R^2$  at about 0.92 and *RMSE* at roughly 520MPa.
- All in all, according to the results' description and outputs of the Taylor diagram, the best model with the combination of *WDC*, *CSAFR*, *DMR*,  $\sigma_3$ , and  $\sigma_d$  is recognized as the most suitable model, and because of this result, the second section of this study was aimed to scrutinize the results of the *M1* model.
- The results of the model *M1* was evaluated deeply as the most appropriate model. As can be gained, both developed *XGB* models could outperform literature (Ghanizadeh *et al.* 2021, Kaloop *et al.* 2019, Maalouf *et al.* 2012), with  $R^2$  equal to at least 0.9973. Interestingly, the lowest value of *RMSE* was for GPR (Ghanizadeh *et al.* 2021) at 116.94 MPa before this study, while this study could gain the extremely lower *RMSE* owned by *BWOA – XGB* model at 55.198MPa, almost lower than a half. At last, the explanations indicate the *BWO* algorithm's capability in the determining the optimal value of *XGB* determinative parameters in  $M_R$  prediction procedure.

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