



Advanced Machine Learning Approaches for Predicting Structural Performance of Reinforced Concrete Columns

Nigar Nagiyeva ^{1*} , Ruslan Hemidov ² 

¹ Department of Informatics, Faculty of Physics and Mathematics, Nakhchivan State University, Nakhchivan, Azerbaijan

² Faculty of Natural Sciences, Lankaran State University, Lankaran, Azerbaijan

Highlights

- Hybrid ML–optimization models developed to predict RC column seismic parameters.
- XGB outperformed RFR in predicting drift and maximum shear strength.
- XGB–MGO achieved the highest accuracy and generalization performance.
- Metaheuristic optimization significantly enhanced prediction stability.
- Model supports reliable, cost-effective seismic design of RC columns.

Article Info

Received: 04 October 2025

Received in revised: 11 November 2025

Accepted: 03 December 2025

Available online: 31 December 2025

Keywords

Reinforced Concrete,
Drift,
Maximum Shear Strength,
Machine Learning,
Metaheuristic Algorithms.

Abstract

Reinforced concrete (RC) columns are key load-bearing elements in buildings and infrastructures, and their seismic performance is primarily characterized by Drift and maximum shear strength (V_{max}). Accurate prediction of these parameters is essential for achieving reliable and cost-effective structural designs. In this study, advanced machine learning (ML) models Random Forest (RFR) and Extreme Gradient Boosting (XGB) are developed and enhanced using two recent metaheuristic optimization algorithms: the Mountain Gazelle Optimizer (MGO) and the Coot Optimization Algorithm (COA). The proposed hybrid frameworks aim to improve prediction accuracy and generalization capability for RC column seismic parameters. Comparative analysis revealed that among standalone models, XGB exhibited superior predictive capability over RFR. Furthermore, the hybrid XGMG model (XGB integrated with MGO) achieved the best overall performance, recording R^2 values of 0.985 for V_{max} and 0.943 for Drift, along with low RMSE values of 15.81 and 0.161, respectively. These findings confirm that integrating metaheuristic optimizers with ML algorithms significantly enhances model efficiency and stability. The developed hybrid model can serve as a reliable tool for engineers and designers in accurately assessing seismic performance, optimizing material use, and ensuring structural safety. Ultimately, this approach contributes to advancing data-driven methodologies for seismic evaluation of RC columns and can be extended to other structural components.

©2025 by the authors.

Published by the [Biljipub publisher \(Zenith Sustainable Energy Institute\)](https://biljipub.com).

This article is an open-access article distributed under the terms and conditions of the [Creative Commons Attribution 4.0 International](https://creativecommons.org/licenses/by/4.0/) (CC BY 4.0).

1. Introduction

1.1. Background

RC columns may be considered one of the most essential parts of the civil infrastructure, which provides the primary support to the buildings, bridges, and other structural systems of the nature of the earth. They have the capability of holding against seismic loading, and they must do so in order to make the structures safe, especially in areas where earthquakes are a common occurrence. However, the problem of accurately predicting the

seismic performance of RC columns resulting from the limited elasticity of structural materials and the uncertainty of seismic forces is quite challenging. The problem becomes particularly serious in the case of large-scale applications, e.g., fast seismic assessment of the road network with a great number of bridges [1]. As a result, there has been an insatiable demand for the development of advanced models that can accurately and efficiently predict the behavior of RC columns and piers under seismic conditions. To address these problems, the

* Corresponding Author: Nigar Nagiyeva
Email: nigar.nagiyeva4@gmail.com

research community has launched a significant amount of experimental work, including pseudo-static experimentation and shaking table experimentation, to investigate the mechanical properties of the RC columns. These have resulted in the creation of clear design formulae through both theoretical study and regression formulae by using experimental data, thus providing essential information for structural design in the field of seismic engineering [2,3]. Still, the inherent limitations of the traditional methods persist. For instance, Priestley et al. [4] pointed out large discrepancies in the prediction of shear strength, and Sezen and Moehle [5], as well as Elwood and Moehle [6], reported discrepancies in the estimation of deformation capacity, hence showing the need for improvement in modeling strategies. The differences encountered are due to the inherent uncertainties and nonlinear nature of RC material behavior. In addition, the shear span ratio [7], longitudinal and transverse reinforcement ratios [8,9], and axial compression ratio [10] significantly influence the seismic performance of RC columns. The interplay of these variables with the effects of constant both vertical and dynamic lateral loads make it harder to accurately design and model RC columns. These are the fundamental research areas of seismic engineering, and advancement in new modeling processes can also result in the increased resilience and reliability of RC columns, which can be used in seismic engineering.

Finite element analysis (FEA) has evolved and become one of the notable methods used to analyses non-linearly in the mechanical analysis of the RC structures [11,12]. In the case of RC columns, two popular methods are prevalent in the modeling of nonlinear behavior, which include the lumped plasticity (LP) hinge approach and the distributed plasticity (DP) hinge approach [13,14]. The LP method is simple but gives rough estimates, whereas the DP method is accurate but numerically consuming and highly sensitive to model parameters and boundary conditions [15]. The disadvantages of the methods can at times cause extremely high estimation errors in estimating the seismic performance of structures made of RCs. One interesting case of these difficulties is the open competition held by Lu et al. [16] to predict the hysteretic response of a three-story RC frame that was tested in the laboratory before. Although comprehensive data on the structure configuration and material properties were also given to the participants, FEA projections that were reported by 30 research groups have had a huge variance with the experimental findings, regardless of the modeling method that was used. The causes of these discrepancies were explained by the complicated mechanisms of damage of RC materials and ambiguities in establishing boundaries and relatedness in real-life structures. To reduce these drawbacks, Ibarra et al. [17]

proposed a simplified LP model that considers the necessary parameters like effective stiffness, pre- and post-peak inelastic deformations. The model has demonstrated itself as a potentially seismic performance simulator of RC structures when proper parameters are employed [18,19]. Nevertheless, the factual correctness of such analyses is not only dependent on the calculative tools of such analysis but also on the skills and experience of the analysts, which are usually enlightened by the experience of past disasters and testing conducted in laboratories. The personal judgment is a factor that influences the estimation of the model parameters, which also differs greatly across research groups.

1.2. Related Work

The adoption of machine learning techniques has gained increasing interest in the civil engineering community and provided fresh perspectives to explain the complex structural behaviours. These have been found in many fields: energy performance analysis [20]; prediction of the mechanical properties of the concrete material [21–27], and estimation of the unconfined compressive strength of soil substrates [28–30]. Kawashima and Oreta [31] showed the capability of ANNs in modeling compressive stress-strain relationships, especially for cases where data is limited. Also, non-parametric models, such as the conditional average estimator (CAE) method [32] and support vector machines (SVMs) [33], have been used to estimate the mechanical properties and seismic performance of structures. Many studies have highlighted the flexibility of machine learning (ML) methods in structural analysis. González and Zapico [34] developed a methodology for seismic damage identification in steel moment-frame structures using modal variables. Reza et al. [35] carried out an extensive parametric study on the limiting states of bridge columns through factorial analysis. Unlike the conventional regression-based equations or expert-driven methodologies, models based on machine learning follow a data-driven paradigm. Such models, analyzing large data sets with abundant sample features, thereby reduce reliance on constrained databases or pre-determined assumptions and lower subjective biases together with experimental inaccuracies.

1.3. Research Objectives

While there has been much development in using machine learning for the prediction of different properties and responses in civil engineering, a large gap remains. This gap concerns the use of ML techniques to predict the drift and maximum shear strength (V_{max}) of RC columns. Filling this gap is important because the accurate prediction of these factors is necessary for the seismic performance assessment and to ensure that the RC structures are safe and effective. To close this gap, this

study proposes a complete framework that combines advanced machine learning models with optimization methods. More specifically, this research uses Random Forest and Extreme Gradient Boosting as the major predictive models, since they can work well with complex, nonlinear data, resist overfitting, and clearly show which features are important. The models are useful in forecasting complex behaviors, such as the performance of structures in the case of an earthquake. MGO and the COA are applied to tune hyperparameters in order to achieve better predictions and work faster. The reason why these algorithms are selected is that they perform well in searching around the world, solving problems in a short amount of time, and they are not prone to local optima, which will solve to give the optimal parameter settings of the base models. In the research, the use of MGO and COA was aimed at improving the performance of the model. These optimizers have been chosen because of the recent accomplishment in solving complex engineering optimization problems. MGO is very much exploratory globally by using adaptive foraging, and COA offers a balance of both convergence speed and diversity of the population. MGO and COA can be considered effective in hyperparameter optimization in machine learning models because they have shown better convergence and resistance to local minima than classical optimizers like GA and PSO. MGO and the COA were utilized in this study to increase model performance. These optimizers have been chosen because of the recent accomplishment in solving complex engineering optimization problems. MGO exhibits strong global exploration capabilities through adaptive foraging strategies, while COA provides a good balance between convergence speed and population diversity. Compared with classical optimizers such as GA and PSO, MGO and COA have demonstrated improved convergence and robustness in avoiding local minima, making them well-suited for hyperparameter tuning in machine learning models.

2. ML-Based Methods

2.1. Random forests (RF)

RF is one of the supervised learning algorithms and an ensemble learning method that generalizes decision trees for classification and regression problems. On training, it forms a large number of decision trees and returns the most frequent class of predictions or the average output given by all the individual trees. A decision tree is arranged in the structure of a tree, either binary or non-binary. Each non-leaf node is a feature test, and every branch is an outcome of the feature on various values; every leaf contains a category. The decision tree starts with a root node, at which the relevant feature attributes of the category to be classified are checked, and then follows the branches according to the values to reach

a leaf node. Eventually, the category held by that leaf node will be considered as the outcome of the decision. A random forest is a set of decision trees independent of each other. The criteria for dividing attributes in the decision tree are based on the Gini index, and the depth of each tree branch is determined by the algorithm parameter d .

The Gini Index at a node within the tree is determined in the following way: For an individual (nominal) split attribute Y_i , let the possible levels be represented as $S_1; \dots; S_j$. The Gini Index for this attribute is computed as Eq. (1):

$$G(Y_i) = \sum_{j=1}^J \Pr(Y_i = S_j) (1 - \Pr(Y_i = S_j))$$

$$= 1 - \sum_{j=1}^J \Pr(Y_i = S_j)^2 \quad (1)$$

The reason for selecting the Random Forest algorithm instead of other machine learning algorithms stems from its various benefits [36]:

- It performs effectively on large datasets and excels in accuracy compared to existing algorithms;
- It can handle issues related to unbalanced class population data sets;
- It provides a robust approach for estimating missing data, ensuring accuracy even when a significant portion

2.2. Extreme Gradient Boosting (XGB)

XGBoost is a gradient boosting machine (GBM) algorithm that is widely regarded as one of the most efficient methods for supervised learning. This algorithm is adaptable and can be used for both regression and classification tasks. Its popularity among data scientists stems from its rapid execution speed, which is due to its ability to perform out-of-core computations. The process works as follows: consider a dataset DS containing m examples and m features, where $DS = \{(X_i, y_i) : i = 1 \dots m, x_i \in S^Z, y_i \in S\}$. Subsequently, the anticipated result of an ensemble tree model can be obtained using these equations:

$$B_{.i} = \phi(X_i) = \sum_{k=1}^K f_k(X_i), \quad f_k \in F \quad (2)$$

K represents a variable that indicates the quantity of trees. f_k represents the $(k - th)$ tree.

To solve the previously mentioned equation, it is essential to reduce the loss and regularization objective by finding the best set of functions.

$$\gamma(\phi) = \sum_i 1(y_i, B_{.i}) + \sum_k \epsilon(f_k) \quad (3)$$

The loss function, denoted as γ , is characterized as the disparity between the predicted output, $\hat{y}_i$, and the true output, y_i .

L is a measure that assesses the intricacy of the model, aiding in the avoidance of overfitting. It is calculated using Eq (4):

$$\varepsilon(f_k) = \alpha T + \frac{1}{2} \lambda \|H\|^2 \quad (4)$$

The variable H signifies the weight allocated to every leaf. T refers to the overall count of leaves.

Boosting is utilized in decision trees throughout the training process to reduce the objective function by adding a new function f as the model progresses in its learning. Therefore, at each iteration (t), a new function (*tree*) is incorporated into the model, as demonstrated by (5-8):

$$\gamma^{(t)} = \sum_{i=1}^n 1(y_i, B_{\cdot i}^{(t-1)} + f_t(X_i)) + \varepsilon(f_t) \quad (5)$$

$$\varepsilon_{\text{split}} = \frac{1}{2} \left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} u_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} u_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} u_i + \lambda} \right] \quad (6)$$

$$g_i = \partial_{B^{t-1}} 1(y_i, B_{\cdot i}^{(t-1)}) \quad (7)$$

$$u_i = \partial_{B^{t-1}}^2 1(y_i, B_{\cdot i}^{(t-1)}) \quad (8)$$

2.3. Coot Optimization Algorithm (COA)

COA is inspired by the coordinated moves of Coots, a kind of waterbird, and is set up with metaheuristic optimization. For finding food materials or reaching targeted positions in water, Coots reflect different movement policies like random, successive, leader-led, and leader-dependent movements. Some such factors are combined with the design of the COA algorithm. Following the recipe, Eq. (9) is applied to generate a random primary majority at the very start of the algorithm's execution [37].

$$\text{CootPos}(i) = \text{rand}(1, M) \times (UB - LB) + LB \quad (9)$$

$\text{CootPos}(i)$ is the position values of a single coot, while M is the problem dimensionality or the number of parameters. UB and LB are the upper and lower bounds of the space in which the search will be performed.

$$UB = [UB_1, UB_2, \dots, UB_M], LB = [LB_1, LB_2, \dots, LB_M] \quad (10)$$

After the initial majority setup, the coots will be rearranged in sequence according to four different motion patterns.

• Random Movement

The initial position of G in this move is generated randomly based on the formula given in Eq. (11):

$$G = \text{rand}(1, M) \times (UB - LB) + LB \quad (11)$$

$$\text{LeaderPos}(i) = \begin{cases} B \times B_3 \times \cos(2\pi R) \times (g_{\text{best}} - \text{LeaderPos}(i)) + g_{\text{Best}} & V_4 < 0.5 \\ B \times B_3 \times \cos(2\pi R) \times (g_{\text{best}} - \text{LeaderPos}(i)) - g_{\text{Best}} & V_4 \geq 0.5 \end{cases} \quad (17)$$

In Eq (17), g_{best} represents the best position that can be attained while V_3 and V_4 are random values selected from the interval $[0, 1]$. The variable V is calculated using the equation outlined in Eq (18):

$$V = 2 - L \times \left(\frac{1}{\text{Iter}}\right) \quad (18)$$

To escape the local optimal solutions, the position is adjusted as described in Eq. (12):

$$\text{CootPos}(i) = \text{CootPos}(i) + D \times R_2 \times (G - \text{CootPos}(i)) \quad (12)$$

R_2 represents a number that is generated randomly within the interval from 0 to 1, and D is calculated using the formula outlined in Eq. (13).

$$D = 1 - L \times \left(\frac{1}{\text{Iter}}\right) \quad (13)$$

- Iter is the maximum allowable number of iterations, while L denotes the number of iterations currently carried out.
- Chain Movement**

To carry out the sequential movement, you can determine the average position of two coot birds by applying the formula specified in Eq. (14):

$$\text{CootPos}(i) = \frac{\text{CootPos}(i-1) + \text{CootPos}(i)}{2} \quad (14)$$

$\text{CootPos}(i-1)$ signifies the location of the subsequent coot within the sequence.

- **Adjusting Position According to the Leader**

In each group, the location of a coot bird shifts in response to the position of the leader, prompting the follower to approach the leader more closely. The choice of the leader is established through the formula specified in Eq. (15):

$$K = 1 + (i \text{ MOD } ML) \quad (15)$$

In Eq (36), K denotes the index for the leader, i represents the identifier for the follower coot bird, and ML refers to the overall number of leaders in the group. During this particular movement, the position of a coot is modified according to the formula given in Eq (16):

$$\begin{aligned} \text{CootPos}(i) &= \text{LeaderPos}(K) \\ &+ 2 \times R_1 \times \cos(2\pi R) \times (\text{LeaderPos}(K) - \text{CootPos}(i)) \end{aligned} \quad (16)$$

As stated in Eq (16), $\text{LeaderPos}(K)$ indicates the position of the selected leader, R_1 is a value randomly chosen from the interval $[0, 1]$, and a different random value, R , is chosen from the range $[-1, 1]$. These values are incorporated into the computation outlined in Eq. (16) to update the position.

- **Leader Movement**

The leader's positions are adjusted according to the principles specified in Eq. (17), allowing for a shift from localized optimal placements to achieving global optimality.

2.4. Mountain Gazelle Optimizer (MGO)

MGO Optimization algorithm inspires elements in principles drawn from mountain gazelles, mainly Bachelor Male Herd; Maternity Herds, solitary territorial male, and Migration for Food, while proposing the methods of optimization techniques. The three kinds of gazelles may be categorized as follows: Maternity Herds, Bachelor male herds, and Solitary Territorial males. A new Gazelle may be incorporated into any category. Here, the representation of the global optimum is considered as the dominant adult male in a herd of gazelles. The bachelor male herds consist of the younger and less competitive members, and thus, it can be assumed that around one-third of the population would present the minimum cost. In addition, solutions from maternity herds also contribute to the algorithm by retaining only the strong ones with high-quality solutions and discarding those whose costs are significantly higher. These processes of optimization are mathematically formulated, and the algorithm skillfully keeps the balance between phases of exploitation and exploration. This allows solutions to get closer to optimality while pursuing exploration via four clearly defined mechanisms [38].

2.4.1. Territorial Solitary Males

As they mature and gain in strength, adult male mountain gazelles become very territorial. Each has his territory, which he defends. Their territories are usually quite apart; thus, clashes and severe combat over the control of females and territory are common. The younger males would try to impose themselves and breed with the females, while the mature males guard their respective territories. It is represented mathematically through Eq. (19), showing territories maintained by male gazelles.

$$TSM = male_{gazelle} - [(ri_1 \times AC - ri_2 \times Y(t)) \times P] \times Cof_r \quad (19)$$

In Eq (19), $male_{gazelle}$ is represented as the position vector, which signifies the best global solution represented by the adult male. The variables ri_1 and ri_2 are random integers that can take on values of either 1 or 2. The vector AC stands for the coefficient vector of the young male herd, calculated using Eq. (20). P is determined through Eq. (21). The chosen coefficient vector, cof_r , is updated with each iteration to improve search capabilities. The process for determining this coefficient vector is outlined by Eq. (22).

$$AC = Y_{ra} \times [r_1] + U_{pr} \times [r_2], \quad ra = \left\lceil \left[\frac{M}{3} \right] \dots M \right\rceil \quad (20)$$

Where Y_{ra} denotes a solution selected at random (a young male) within the defined limits of ra . U_{pr} indicates the mean number of search agents, calculated as $\lceil \frac{M}{3} \rceil$. Here, M represents the total count of gazelles, while r_1 and r_2 are random values that fall between 0 and 1.

$$P = M_1(D) \times \exp \left(2 - Iter \times \left(\frac{2}{MaxIter} \right) \right) \quad (21)$$

Eq. (sition vector determines the potential solutions21) integrates different variables linked to the dimensions of the problem. M_1 represents a randomly generated number that adheres to a standard distribution, and the equation includes the exponential function exp . $MaxIter$ signifies the total count of iterations, whereas $Iter$ denotes the present iteration number in the process.

$$Cof_i = \begin{cases} (c + 1) + r_3, \\ c \times M_2(D), \\ r_4(D), \\ M_3(D) \times M_4(D)^2 \times \cos((r_4 \times 2) \times M_3(D)), \end{cases} \quad (22)$$

$$c = -1 + Iter \times \left(\frac{-1}{MaxIter} \right) \quad (23)$$

r_3, r_4 , and $rand$ are variables that take on random values between 0 and 1. N_2, N_3 , and N_4 represent random variables drawn from a normal distribution, which relate to the problem's dimensions. $MaxIter$ specifies the overall count of iterations to be performed, while $Iter$ signifies the present iteration count.

$$MH = (AC + Cof_{1,r}) + (ri_3 \times male_{gazelle} - ri_4 \times Y_{rand}) \times Cof_{1,r} \quad (24)$$

AC refers to the vector that signifies the influence of young males, computed using Eq. (20). The coefficient vectors, $Cof_{2,r}$ and $Cof_{3,r}$, are independently chosen at random. The values of ri_3 and ri_4 are random integers that can either be 1 or 2. The $male_{gazelle}$ signifies the best overall solution (adult male) in this iteration. Additionally, Y_{rand} pertains to the position vector of a gazelle that has been randomly selected from the whole population.

2.4.2. Bachelor Male Herds

As male gazelles attain maturity, they generally establish territories and seek to breed with female gazelles. In this period, younger male gazelles might engage in confrontations with older males, competing for control over territory and the opportunity to mate with female gazelles. The way gazelles exhibit this behavior is specifically represented by Eq. (25).

$$BMH = (Y(t) - D) + (ri_5 \times male_{gazelle} - ri_6 \times AC) \times Cof_r \quad (25)$$

$$D = (|Y(t)| + |male_{gazelle}|) \times (2 \times r_6 - 1) \quad (26)$$

Where $Y(t)$ represents the position vector of the gazelle during the current iteration. The variables ri_5 and ri_6 are random integers that can either be 1 or 2. The position vector of the male gazelle, which denotes the optimal solution, is represented as $male_{gazelle}$. Additionally, r_6 is also a random number within the specified range [0,1].

2.4.3. Migration to Search for Food

Mountain gazelles exhibit a natural inclination to search for food, frequently undertaking long travels to

locate adequate food sources or participating in migration. Their remarkable speed and leaping skills contribute significantly to this behavior, as is mathematically demonstrated in Eq. (27).

$$MSF = (ub - lb) \times r_7 + lb \quad (27)$$

Where, ub and lb define the upper and lower limit of the issue, respectively. Additionally, r_7 is a randomly selected integer ranging between 0 and 1.

3. Data Preparing

3.1. Presentation of Data

For the prediction of the drift ratio and the maximum shear strength, V_{max} , of RC columns under different loads, a comprehensive dataset was prepared by compiling experimental data from pseudo-static cyclic tests conducted globally. The pseudo-static cyclic tests are carried out to assess hysteretic behavior and seismic performance of RC columns in buildings and bridges.

The dataset was derived from previous studies [39] and included cyclic test results sourced from the NEEShub database [40] and the PEER database [41]. The selection criteria for including test data in this study are as follows:

1. Only rectangular cross-section RC columns were considered; columns with other cross-sectional shapes, such as circular, were excluded.
2. The RC columns sustained constant axial loads and unidirectional cyclic lateral forces; tests involving biaxial lateral forces or variable axial loads were omitted.
3. The specimens were fully loaded up to failure, which was taken as a decrease in load-carrying capacity of over 20 percent compared to the greatest strength.
4. Specimen data were in detailed form, with geometric dimensions, reinforcement data, and hysteretic curve data.
5. All the specimens were produced with normal concrete without steel fibers or other additives.

Indeed, using these criteria, 1163 initial results of cyclic tests were gathered. Following preprocessing, which involved the elimination of samples containing

missing data, the number of samples left to train, test, and validate the ML models was 989.

The dataset includes 15 input variables and two output variables:

- **Input variables:**

- ❖ **Geometric properties:** Width of column (B), Depth of column (D), Length of column (L), Hoop spacing (s), L/d ratio.

- ❖ **Reinforcement properties:** Longitudinal reinforcement ratio (ρ_{oul}), Transverse reinforcement ratio (ρ_{ousv}), Development length (l_d), Steel yield strengths (f_y, f_{yh}), Tensile strength of steel (T_d).

- ❖ **Material and load properties:** Concrete compressive strength (f_c), Axial load ratio ($P/f_c A_g$), Shear span ratio (s/b).

- **Output variables:** Drift ratio (Drift) and maximum shear strength (V_{max}).

The data obtained had a comparatively broad distribution of the key features. All input and output variables are summarized in Table 1 in terms of their statistical properties, such as the maximum, minimum, mean, standard deviation, and skewness. Fig. 1 is a correlation matrix that was created to assess the interrelationships among variables. It was noted that column sectional property, including B (Width) and D (depth), had the highest positive relationship with output variables, especially the drift ratio.

The data the research works with in this study is somewhat limited by its nature. The information, to a large extent, is gathered through experimental studies found in the literature, possibly leading to biases that are associated with geographic construction activities, material quality, and detailing of reinforcement. In addition, the dataset mainly contains RC columns of more traditional geometry acting in quasi-static lateral loading, which might not represent the complexity of dynamic seismic phenomena fully. In that way, the proposed models demonstrate high predictive accuracy, but their applicability to other structural arrangements or loading conditions is to be confirmed in further studies with larger and more diverse datasets.

Table 1. The summary of the statistical properties of input and output variables.

Components	Units	Properties				
		Max	Min	Mean	St. Dev	skewness
Width	(B, m)	0.914	0.080	0.284	0.104	1.314
Depth	(D, m)	0.914	0.100	0.298	0.107	1.172
Length	(L, m)	3.500	0.160	1.051	0.561	0.855
Hoop spacing	(s, m)	0.457	0.020	0.099	0.075	2.994
l_d	(diameter)	0.032	0.006	0.016	0.005	0.702
l_N	-	40.00	4.000	9.103	5.149	2.949
ρ_{oul}	-	0.069	0.003	0.022	0.009	2.108
T_d	(m)	0.016	0.003	0.008	0.002	0.774
ρ_{ousv}	-	0.073	0.001	0.017	0.012	1.284
f_y	(MPa)	1510	317.917	443.90	83.84	2.77

f_{yh}	(MPa)	1470	220	483.66	210.77	2.59
f_c	(MPa)	160.9	13.097	52.274	27.753	0.915
$P/f_c A_g$	-	0.900	0.000	0.283	0.175	0.418
s/b	-	1.650	0.083	0.342	0.201	1.639
L/d	-	13.200	1.000	3.662	1.932	1.669
V_{max}	-	630.15	4.170	206.18	130.31	0.982
Drift at V_{max}	-	3.400	0.273	1.499	0.639	0.737

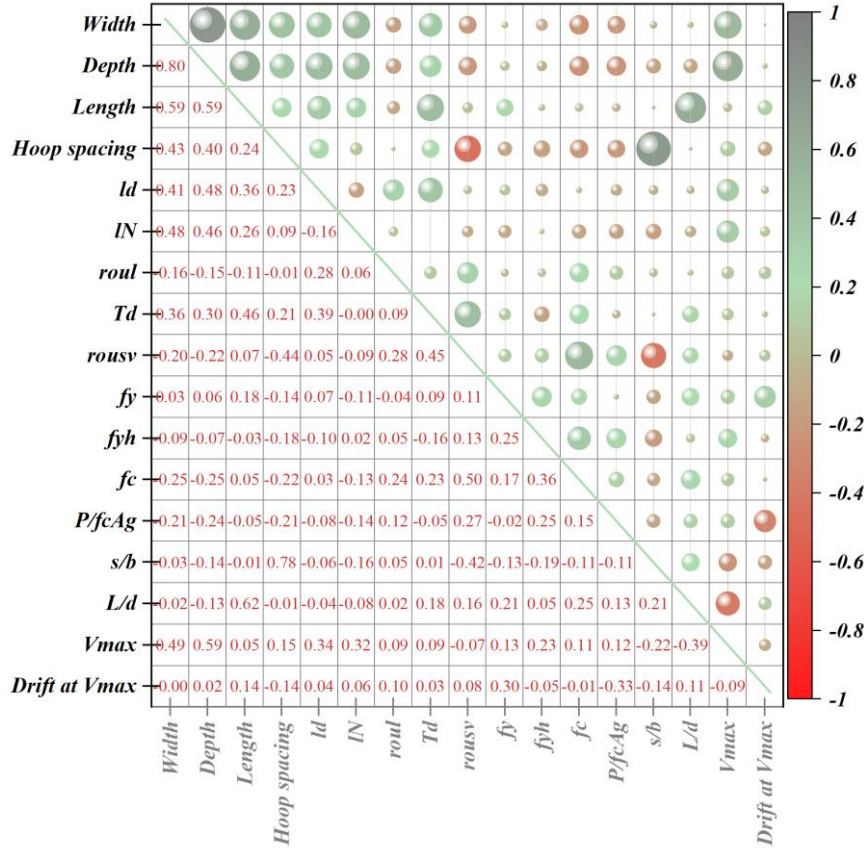


Fig. 1. Illustration of the correlation between the input and output parameters.

3.2. K-Fold Cross Validation

In this study, the use of powerful validation methodologies is highlighted since the study used 989 samples, which is extremely significant in the context of confirming the reliability and applicability of the predictive models, particularly in datasets of different sizes. In order to evaluate the performance of the models effectively, a 5-fold cross-validation strategy was applied to provide a systematic way of testing their ability to generalize to data that has never been seen before. The k-fold cross-validation technique partitions a dataset into several K subsets (known as folds), which are ideally of equal size [42]. In this experiment, K equals 5—that is, the dataset was folded into five partitions. During each execution, four of the folds were used to train the algorithms, while one-fold was used as the validation data, equivalent to 80% and 20% of the data. This process was carried out five times in total, with each fold serving once as the validation data. The average performance

across all folds was used as the final estimate of the model's prediction performance.

Tables 2 and 3 present the detailed results for the cross-validation process in the prediction of V_{max} and Drift ratio, respectively. The iteration had other performance measures computed, like R2 and RMSE, hence a comprehensive analysis regarding the accuracy and reliability of the models. In predicting V_{max} , the RFR and XGB models performed well in all the folds, with Fold 1 indicating the best performance in terms of R2 and RMSE. This is indicative that the models were aware of the key trends in the training data and were successful on the validation data in this fold. Table 3 shows the findings of the 5-fold cross-validation to predict the drift. In the case of the RFR model, Fold 2 gave the most refined output in terms of R2 and RMSE. Conversely, the Fold 4 was the best predictor in the XGB model. These variations indicate why it is essential to examine multiple folds in an attempt to identify the model settings and data subsets in which the most reliable predictions are obtained.

Table 2. The outcomes of the K-fold cross-validation for V_{max} prediction.

<i>K-fold</i>	Modeling name			
	<i>RFR</i>		<i>XGB</i>	
	<i>RMSE</i>	<i>R²</i>	<i>RMSE</i>	<i>R²</i>
<i>K1</i>	29.211	0.951	25.731	0.962
<i>K2</i>	30.804	0.947	26.239	0.960
<i>K3</i>	31.998	0.941	29.298	0.950
<i>K4</i>	29.748	0.950	27.848	0.955
<i>K5</i>	33.188	0.937	31.004	0.944

Table 3. The outcomes of the K-fold cross-validation for Drift prediction.

<i>K-fold</i>	Modeling name			
	<i>RFR</i>		<i>XGB</i>	
	<i>RMSE</i>	<i>R²</i>	<i>RMSE</i>	<i>R²</i>
<i>K1</i>	0.216	0.893	0.180	0.920
<i>K2</i>	0.202	0.909	0.186	0.916
<i>K3</i>	0.235	0.870	0.200	0.902
<i>K4</i>	0.222	0.888	0.170	0.930
<i>K5</i>	0.221	0.885	0.179	0.921

4. Assessment Criteria

To adequately evaluate the performance of the developed models, different metrics are employed in measuring the accuracy and reliability of the models. The metrics examine the similarity of the predicted values with the actual ones and determine the magnitude and the variability of errors. Such indicators as Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), Theil U (UI), Mean Absolute Relative Error (MARE), Scatter Interval (SI), and Mean Normalized Bias (MNB) are evaluated. A combination of these measures provides a balanced picture of the performance of the models, which is meaningful since it considers the important aspects of minimizing errors, managing any uncertainty, and preventing systematic biases [43,44].

$$MNB = \frac{1}{n} \sum_{i=1}^n \frac{s_i - p_i}{R} \quad (28)$$

$$MARE = \frac{1}{n} \sum_{i=1}^n \frac{|s_i - p_i|}{|\bar{s} - \bar{p}|} \quad (29)$$

$$SI = \frac{RMSE}{\bar{s}} \quad (30)$$

$$R^2 = \left(\frac{\sum_{i=1}^n (s_i - \bar{s})(p_i - \bar{p})}{\sqrt{[\sum_{i=1}^n (s_i - \bar{s})^2][\sum_{i=1}^n (p_i - \bar{p})^2]}} \right)^2 \quad (31)$$

$$UI = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (s_i - p_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n p_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n s_i^2}} \quad (32)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (s_i - p_i)^2} \quad (33)$$

The variables that are involved in the evaluation metrics are very important in analyzing the performance of the model. In this case, n is the number of data samples taken in full, whereas s_i and p_i are the actual and predicted values of the i th sample. The abbreviations $\bar{s}$ and $\bar{p}$ represent the mean of the observed and forecasted values among the samples. Also, R is a reference value that is used to normalize the bias in determining the MNB.

5. Results and Discussion

5.1. The outcomes of the hyperparameters and convergence curves

Hyperparameters are critical parameters that characterize the form and behaviour of a machine learning model, including the number of layers, the number of neurons per layer, and the learning rate. Contrary to model parameters that are learned in the course of training, hyperparameters are specified before training commences, and their influence on the performance of the model is great. These settings are important to optimize and ensure that the model is accurate and efficient. Different hyperparameter combinations can be tested in a systematic way by methods such as grid search and random search, and are useful to identify hyperparameter combinations that provide more reliable and accurate predictions. Models are capable of achieving their potential predictive performance by adjusting these settings. The present research employs two base models to estimate the values of Vmax and Drift of RC columns. Table 3 shows the hyperparameters that have been optimized to use in both outputs of the RFR-based models. These are models that have three major hyperparameters, namely, $n_estimators$, max_depth , and $min_samples_split$.

Equally, the optimal values of hyperparameters of the XGB-based hybrid models are presented in Table 4. These models are adjusted by seven hyperparameters,

which are `n_estimators`, `max_depth`, `learning_rate`, `colsample-by-tree`, `subsample`, `reg_alpha`, and `reg_lambda`.

Table 4. The results of hyperparameters for RFR-based models of V_{max} and Drift.

<i>Hyperparameter</i>	<i>Target</i>	<i>Models name</i>	
		<i>RFMG</i>	<i>RFCO</i>
<i>n_estimators</i>	V_{max}	206	109
	Drift	999	271
<i>max_depth</i>	V_{max}	224	126
	Drift	999	350
<i>min_samples_split</i>	V_{max}	2	2
	Drift	2	2

Table 5. The results of hyperparameters for XGB-based models of V_{max} and Drift.

<i>Hyperparameter</i>	<i>Target</i>	<i>Models name</i>	
		<i>XGMG</i>	<i>XGCO</i>
<i>n_estimators</i>	V_{max}	658	999
	Drift	194	568
<i>max_depth</i>	V_{max}	999	684
	Drift	930	338
<i>learning_rate</i>	V_{max}	0.034	0.724
	Drift	0.931	0.560
<i>colsample_bytree</i>	V_{max}	0.889	0.704
	Drift	0.152	0.352
<i>subsample</i>	V_{max}	0.986	0.887
	Drift	0.863	0.744
<i>reg_alpha</i>	V_{max}	0.999	0.681
	Drift	0.782	0.793
<i>reg_lambda</i>	V_{max}	0.903	0.838
	Drift	0.001	0.873

Figs. 2 and 3 present the convergence plots for predicting V_{max} and Drift using combinations of machine learning models and optimization algorithms. These plots show the changes in RMSE over 200 iterations for the RF and XGB models optimized with the MGO and COA algorithms. In Fig. 2, when concentrated on V_{max} , the XGB-MGO (XGMG) hybrid model was the best performing, with the lowest RMSE was 10.2, the best predictive accuracy, and efficient convergence. The sharp reduction of RMSE points to the high speed of error minimization of the model, which gives importance to the strength of the optimization process. The next model was the RF-MGO (RFMG) hybrid with an RMSE of 17.774, with a reasonable accuracy but a slower convergence rate than XGMG. Conversely, RF-COA (RFCOA) and XGB-COA (XGCO) hybrid models also recorded higher values of RMSE of 27.79 and 21.284, respectively, which means that the COA was not effective in streamlining these models to predict V_{max} . Equally, in the convergence of Drift in Fig. 3, the XGMG hybrid model once again performed better than the rest with the lowest RMSE of 0.123. Its convergence curve indicates that it minimizes

errors, and it has a very good optimization process. RFMG model converged with an RMSE of 0.161, which demonstrated good performance but a little less efficient convergence compared to XGMG. Meanwhile, the RFCO and the XGCO models obtained the RMSE of 0.19 and 0.153, respectively. COA-optimized models still did not work as well as MGO-optimized models, although they were better at Drift predictions compared to V_{max} .

Besides predictive performance, the cost of computation of every model was evaluated. Single-model strategies, such as XGB and RFR, had a shorter runtime because optimization is not conducted, and thus, it is applicable in situations where fast predictions are needed. XGB with MGO (XGMG) and XGB with random forest (XG) were found to demonstrate high accuracy, although they required more time to compute, as the model's required iteration before achieving the optimum value. The findings indicate an accuracy-efficiency trade-off, which gives engineers and researchers viable advice on the choice of models used in forecasting seismic performance of RC columns.

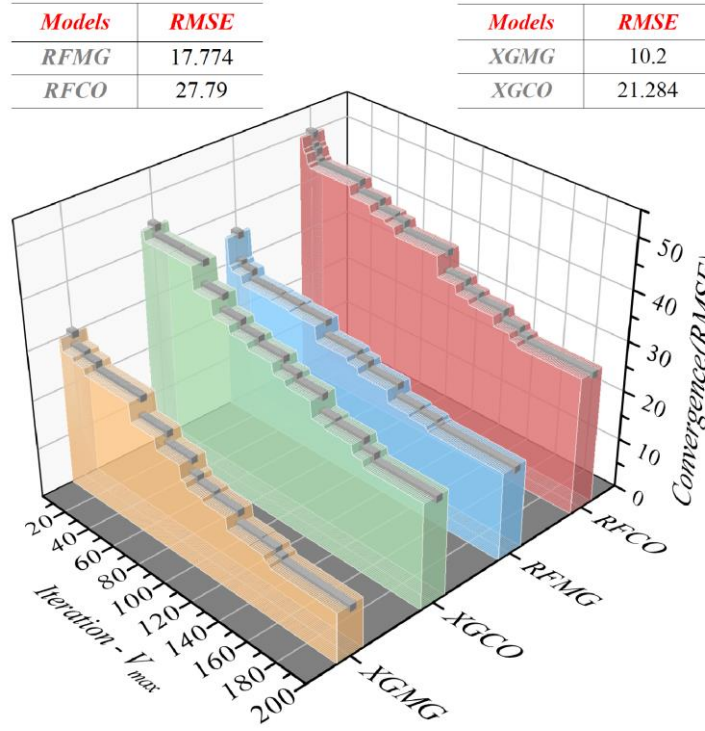


Fig. 2. The 3D plots for assessing the convergence curves of the RF-based and XGB-based hybrid models for V_{max} .

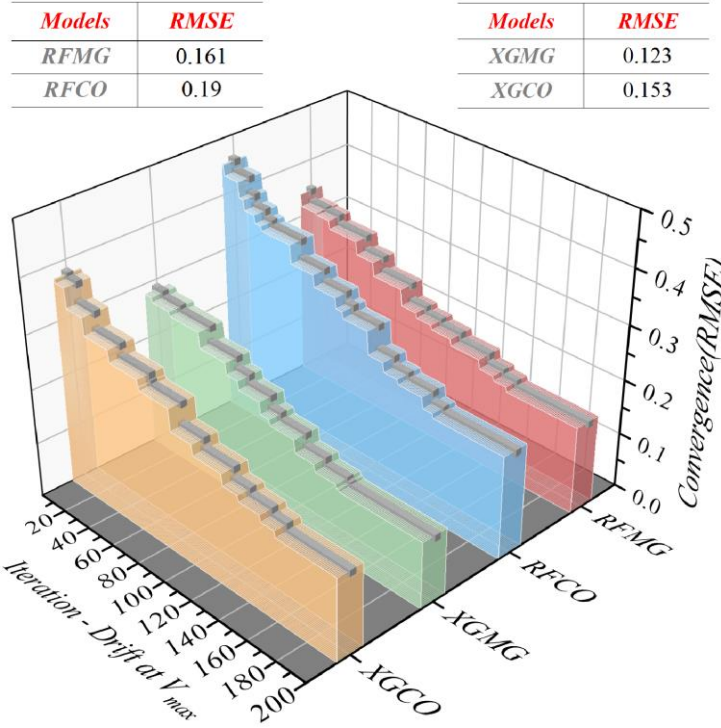


Fig. 3. The 3D plots for assessing the convergence curves of the RF-based and XGB-based hybrid models for Drift.

5.2. The results of the evaluation metrics for comparing the performance of predictive models.

This paper presents hybrid predictive models in order to predict the Maximum Shear Strength (V_{max}) and Drift of RC columns using a combination of RF and XGB with MGO and COA. Such combinations enhance the power of machine learning and metaheuristic optimization in order to attain high predictive ability. To be completely statistically validated, six evaluation

metrics, as discussed in the foregoing section, were employed. The results reveal the high efficiency of these hybrid models in improving the prediction accuracy, a strong framework for the seismic evaluation of RC columns. The following sections show the assessment measures of V_{max} and Drift forecasts in tables and figures.

❖ V_{max} Prediction

Table 6 represents the performance of a single and hybrid model in predicting the V_{max} of RC columns, which was tested during the training, validation, and

testing stages and based on the six major metrics: RMSE, R², Theil U (UI), SI, and MNB. These measures measure the accuracy, error minimization, and reliability of the models. The single models RF and XGB have strong predictive capabilities, with XGB able to perform better than RF on most measures. To illustrate this, XGB has a smaller RMSE of 29.908 than RF of 32.239 and a marginally higher R² of 0.948 than the R² of 0.936, which implies that it minimizes errors and explains more variance than RF, in which the results are worse. Nevertheless, the single models possess certain shortcomings, especially in improved MARE and UI values when undergoing the testing stage. Combining MGO and COA with RF and XGB greatly increases their prediction. To illustrate, the RFMG hybrid model has a high performance in all metrics, recording significant

gains in RMSE, R², and MARE. In the course of testing, RFMG gets an RMSE of 21.275, an R² of 0.972, and a MARE of 15.127, which indicates a high level of accuracy and low level of error variability. Moreover, it has lower SI values, which means it has a better generalization ability. The XGMG hybrid model is the most successful of the models in that it provides the lowest RMSE of 15.810 and the highest R² of 0.985 during the test. These findings demonstrate the outstanding capacity of XGMG to capture complex data trends, reduce errors in predictions, and be highly reliable at all stages.

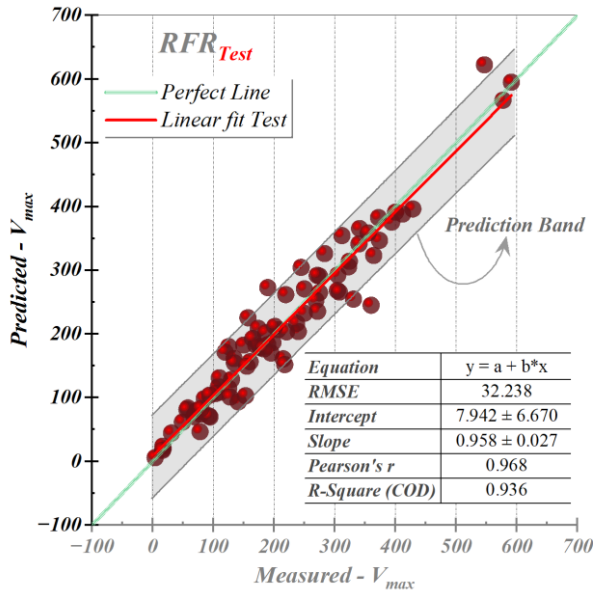
The prediction accuracy is high, which allows engineers to make accurate and well-informed judgments on the structural design, seismic retrofitting, and safety assessment, and, therefore, increase the resilience and minimise the chances of structural failures.

Table 6. The outcomes of the evaluation metrics for V_{max} prediction.

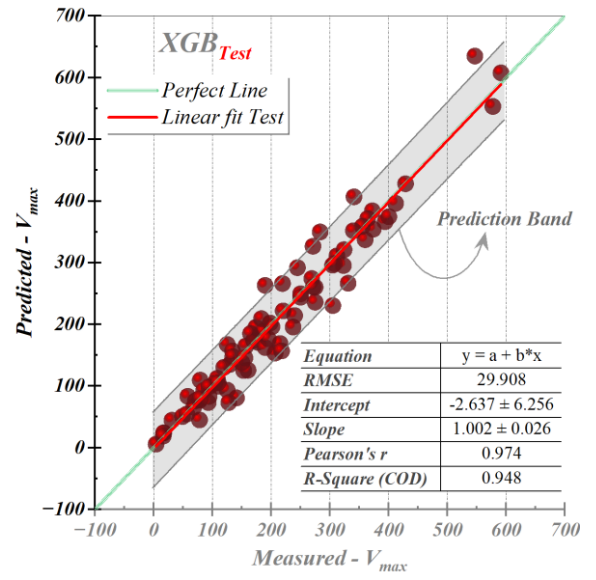
<i>Model</i>	<i>Phase</i>	<i>Index values</i>					
		<i>RMSE</i>	<i>R²</i>	<i>MARE</i>	<i>Theil-u</i>	<i>SI</i>	<i>MNB</i>
<i>RFR</i>	Train	28.515	0.955	17.859	0.217	0.022	28.515
	Validation	31.458	0.935	23.304	0.256	0.042	31.458
	Test	32.239	0.936	23.535	0.253	0.015	32.239
<i>RFMG</i>	Train	16.921	0.985	10.248	0.129	0.016	16.921
	Validation	20.408	0.973	14.382	0.166	0.029	20.408
	Test	21.275	0.972	15.127	0.167	0.020	21.275
<i>RFMO</i>	Train	27.403	0.964	19.070	0.209	0.036	27.403
	Validation	26.008	0.961	19.703	0.212	0.064	26.008
	Test	32.239	0.939	23.735	0.253	0.048	32.239
<i>XGB</i>	Train	24.784	0.965	16.499	0.189	0.007	24.784
	Validation	28.520	0.946	20.794	0.232	0.009	28.520
	Test	29.908	0.948	21.185	0.235	0.007	29.908
<i>XGMG</i>	Train	8.183	0.996	2.024	0.062	0.000	8.183
	Validation	15.984	0.984	11.190	0.130	0.005	15.984
	Test	15.810	0.985	10.919	0.124	0.008	15.810
<i>XGCO</i>	Train	19.839	0.977	4.476	0.151	0.002	19.839
	Validation	22.862	0.969	16.614	0.186	0.039	22.862
	Test	29.323	0.949	20.159	0.231	0.009	29.323

Fig. 4 provides a closer examination of the estimated and observed values of V max in the course of the test, as the performance of six models is displayed. The scatter plots have an ideal reference line ($Y = X$), a linear fit line, and a projection band to give a comprehensive assessment of the accuracy of each model. The model of RFR shows fair prediction ability, where the RMSE is at 32.238, and the R² is at 0.936, which means that it is a good measure of predicting the actual values. Nonetheless, its slope of 0.958 and Pearson r of 0.968 mean that it is underestimated in some areas. The fact that the values do not exactly cluster around the reference line highlights the fact that the model is weak in being able to explain all the variability in V max. The XGB model has a better performance with an RMSE of 29.908

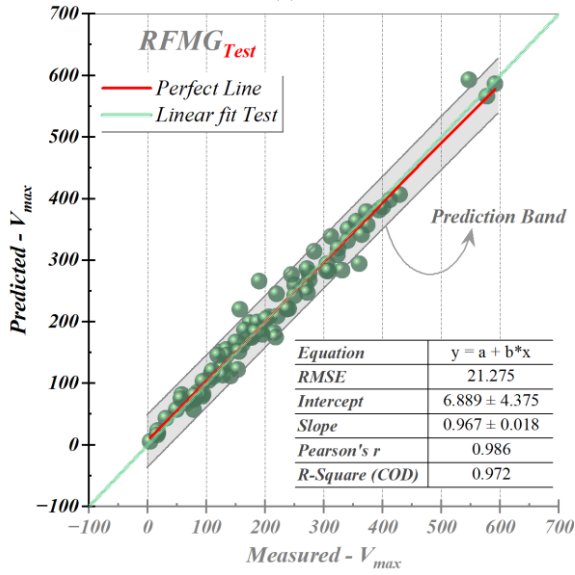
and a higher value of R² of 0.948. A slope of 1.002 that is closer to one indicates a higher degree of accuracy in the prediction and the actual value, whereas a Pearson r of 0.974 attests to the strong association. However, some data points fall outside of the prediction band and reveal the fact that there is still room to optimize. On the other hand, the XGMG hybrid model performs better in comparison with other models, having an RMSE of 15.810 and an R² of 0.985. The high slope of 0.996 and Pearson r of 0.992 indicate the high effectiveness of the model in predicting Vmax with very few deviations. The thick concentration of the data points along the ideal line and in the band of prediction highlights the credibility and accuracy of the data.



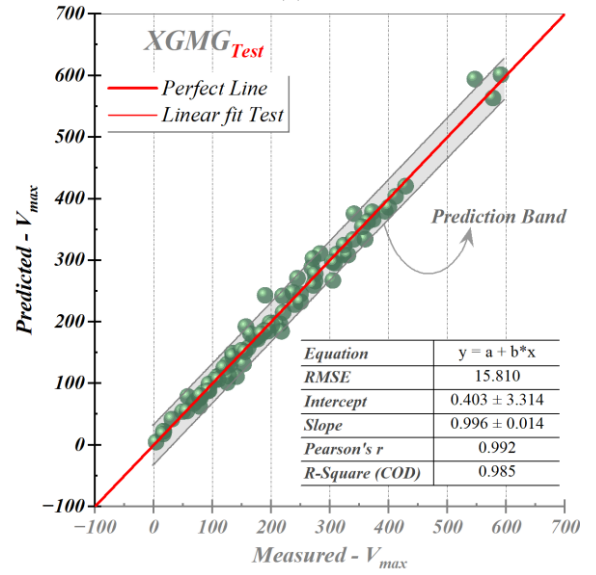
(a)



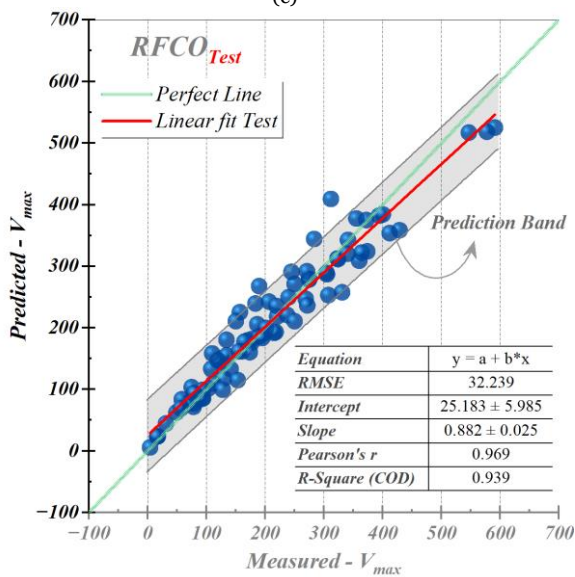
(b)



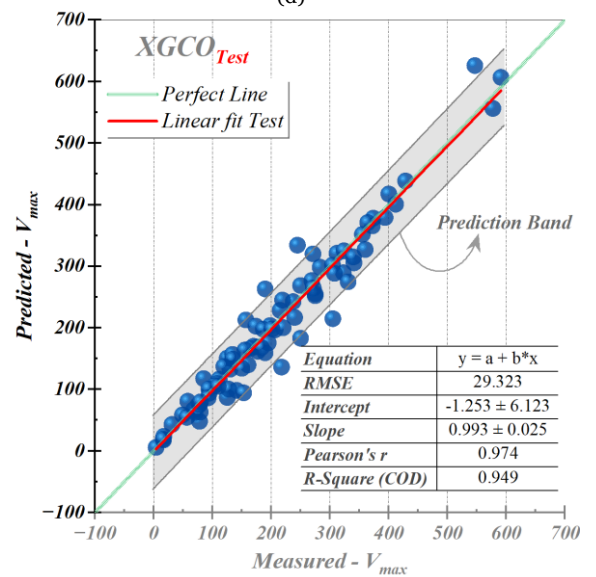
(c)



(d)



(e)



(f)

Fig. 4. The Scatter plots for correlation between the measured and predicted values in the test phase of the V_{max} .

The measured Vmax has been compared with those of the different models in the test stage, as shown in Table 7, and XGMG has higher accuracy. XGMG estimates a maximum Vmax of 635.15, which has a +7.45% difference with the measured maximum (591.05) and a mean of 204.89 and a deviation of a -1.11% of the difference with the measured mean (207.20). Its standard deviation (130.83) is very close to the measured variability (127.19) with a difference of +2.87% and this is to shows its ability

to capture the dispersion of data. The other models, like RFR and RFCO, have more deviations, particularly in the extreme values, and this indicates their limitations. XGMG is very useful in estimating both central tendencies and variability, which is especially useful in real-time seismic, and therefore it can be used to make reliable estimates of peak structural demands and the development of strong designs to endure extreme loading conditions.

Table 7. The comparison between the measured and predicted values for the test phase of V_{max} prediction.

Statistical Analysis	Measured	Modeling name					
		RFR	RFMG	RFCO	XGB	XGMG	XGCO
Max	591.05	622.20	593.15	525.38	635.15	601.18	625.75
Min	4.17	5.98	5.85	5.98	5.95	5.04	5.77
Mean	207.20	206.50	207.20	207.95	204.89	206.78	204.48
St. dev	127.19	125.95	124.71	115.75	130.83	127.66	129.61
Skewness	0.81	0.97	0.88	0.59	0.98	0.89	0.98

Table 8 shows the comparison between the statistical characteristics of the errors committed by six predictors, RFR, RFCO, RFGM, XGB, XGCO, and XGMG, in the testing phase. The findings indicate that there is considerable variability in predictive accuracy and reliability between the models, with XGMG as the most resistant one. The maximum absolute error (Max ABS) indicates that the model XGMG (maximum error of 35.00) is the best, followed by XGCO (38.50) and the RF-based models (e.g., RFR maximum error = 43.76 and RFCO maximum error = 43.75). On the mean error

(Mean), the XGMG (1.39) has a weaker performance than the XGCO model, with an error is 0.6. But this is filled in by XGMG, which has the lowest standard deviation at 10.76, which is the smallest of all the models. This small variability testifies to its unmatched consistency in comparison with XGB (18.49) and RFCO (18.70). The skewness also indicates the superiority of XGMG. Although XGMG (1.24) shows slight preferences towards under-predictions, it is quite balanced in comparison with RFGM (1.08) and much better than RFCO (0.70), which means that it is more accurate in erring.

Table 8. The statistical properties of the errors that occurred in models for the test phase of V_{max} prediction.

Components	Properties				
	Max (ABS)	Min (ABS)	Mean	St. dev	Skewness
RFR	43.76	0.05	3.30	19.5	0.40
RFMG	40.25	0.12	2.91	14.21	1.08
RFCO	43.75	0.49	6.47	18.70	0.70
XGB	42.70	0.05	1.00	18.49	0.30
XGMG	35.00	0.03	1.39	10.76	1.24
XGCO	38.50	0.06	0.6	17.27	0.31

Fig. 5 shows a box plot that offers a comprehensive view of the distribution of the errors in the six models at the test stage and combines a box plot with a kernel density estimation. Such a combination is successful in emphasizing both the statistical summaries and the underlying distribution shapes. The violin shape in the RFR model was the widest, implying a wide error distribution and a high variance. The form of its lengthy whiskers was a sign of extreme error values, which is in line with the large range of error already seen above (-35 to 42). The XGMG model, on the other hand, had a significantly narrower violin, a more concentrated error

distribution, and less variation. The shorter whiskers emphasized the effectiveness of the MGO in the stabilization of predictions and the extreme deviations. More so, the near coincidence of mean and median in the XGMG model accentuated its moderate error characteristics. This was reflected in the boxplot IQR, where 25-75 percent of RFR model errors were between 6.99-13.788, but the IQR of the XGMG model was very small, and 3.513-4.609. This narrower range indicated the greater predictive stability and the decreased range of errors of the XGMG model.

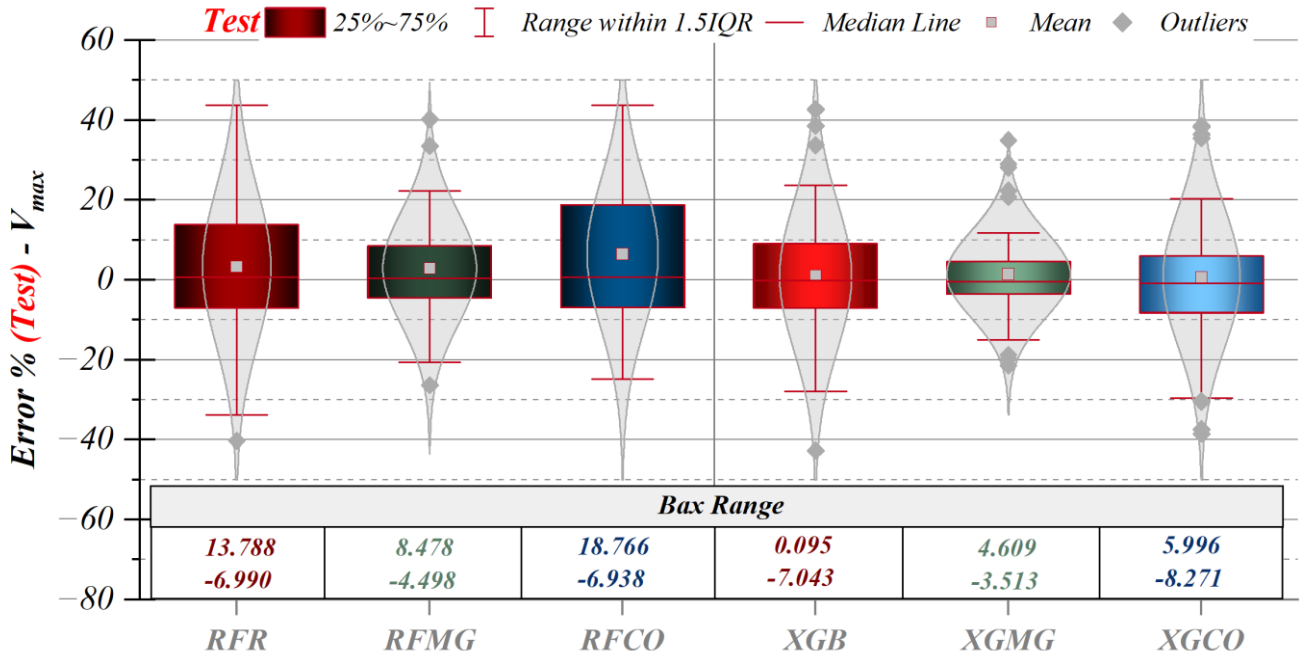


Fig. 5. The box and distribution plots for error values of the models in the test phase of V_{max} prediction.

❖ Drift Prediction

Table 9 identifies how different models of single and hybrid machine learning will perform in predicting Drift, which is an important parameter in assessing the deformation capacity of structures and their seismic performance. Of the individual models, XGB is more accurate than RFR with a lower RMSE of 0.203 and a higher R^2 of 0.906. Nevertheless, these individual models have weaknesses in the reduction of errors and generalization, indicating that more elaborate hybrid methods are required.

Both the hybrid models, particularly those with the help of MGO, demonstrate a tremendous improvement in prediction accuracy. The XGMG model is the best performing in all the metrics, having the lowest RMSE of 0.161 and the highest R^2 of 0.943 in the testing phase,

which indicates that it best predicts the intricate patterns and produces the least error. Likewise, RFMG has significant improvement compared to RFR; its test RMSE is 0.177, and its R^2 equals 0.929, indicating that it has a higher ability to shrink the variation in error compared to RFR and offer a higher reliability.

Both seismic risk management and structural performance assessment have many practical implications of accurately predicting Drift. Such models as the XGMG deliver accurate and effective Drift estimates that provide insight into the decision-making regarding seismic retrofitting, safety evaluation, and assigning resources. This degree of precision is critical in the creation of strong structures and the prevention of possible harm in the earthquake-prone regions.

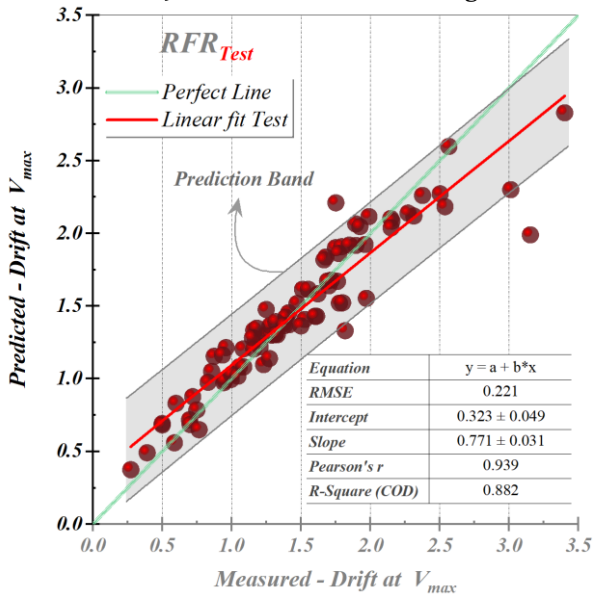
Table 9. The outcomes of the evaluation metrics for Drift prediction.

Model	Phase	Index values					
		RMSE	R^2	MARE	Theil-u	SI	MNB
RFR	Train	0.203	0.912	0.143	0.312	0.025	0.203
	Validation	0.169	0.912	0.130	0.298	0.014	0.169
	Test	0.221	0.882	0.142	0.364	0.019	0.221
RFMG	Train	0.162	0.948	0.115	0.249	0.025	0.162
	Validation	0.134	0.946	0.104	0.237	0.014	0.134
	Test	0.177	0.929	0.115	0.291	0.020	0.177
RFCO	Train	0.191	0.924	0.130	0.297	0.023	0.191
	Validation	0.151	0.934	0.120	0.266	0.016	0.151
	Test	0.210	0.889	0.135	0.345	0.022	0.210
XGB	Train	0.162	0.936	0.095	0.254	0.002	0.162
	Validation	0.189	0.926	0.136	0.283	0.026	0.189
	Test	0.203	0.906	0.138	0.339	0.020	0.203
XGMG	Train	0.113	0.969	0.030	0.177	0.002	0.113
	Validation	0.149	0.958	0.115	0.223	0.034	0.149
	Test	0.161	0.943	0.113	0.268	0.013	0.161

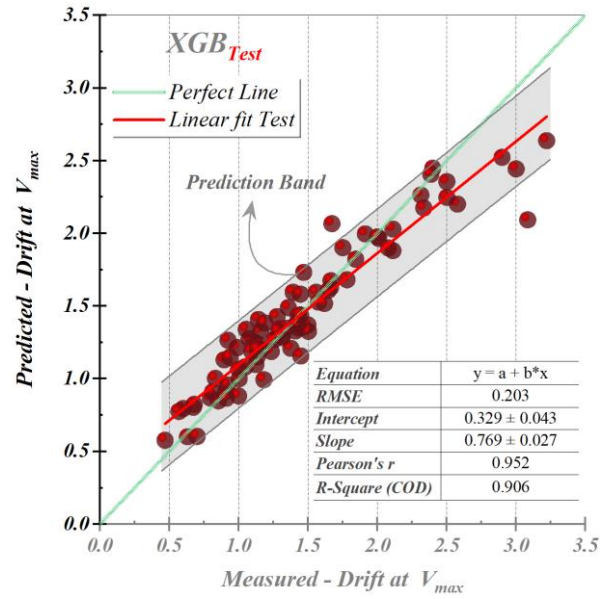
	Train	0.147	0.947	0.086	0.230	0.001	0.147
<i>XGCO</i>	Validation	0.162	0.947	0.124	0.243	0.028	0.162
	Test	0.183	0.917	0.129	0.306	0.012	0.183

Fig. 6 is a comparison of the predicted and actual Drift values in the test phase (six models), and the results are presented in the form of scatter plots, which consist of a perfect reference line ($Y = X$), a linear fitting, and a prediction band in an attempt to make an extensive evaluation. The RFR model has a good performance with RMSE of 0.221, R^2 of 0.882 but it has slight underestimation as the slope is 0.771 and Pearson r of 0.939. The variation in the data points implies that there is a minimal capacity to capture the variability of Drift. XGB is more effective as the model has an RMSE of 0.203 and an R^2 of 0.906. It has a better alignment and

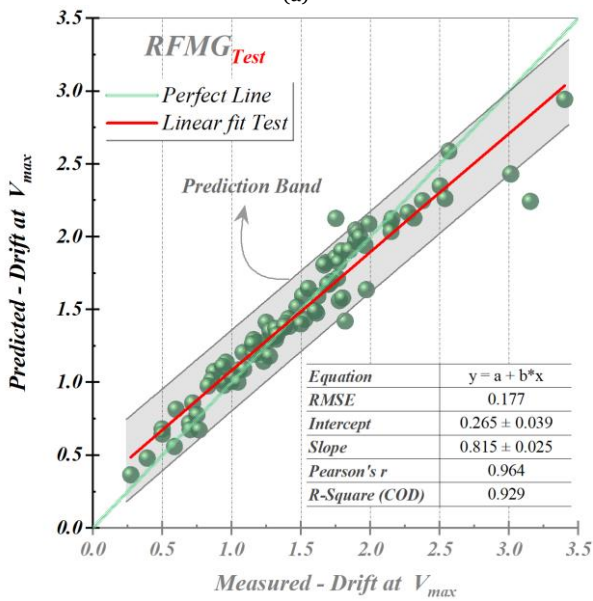
correlation, represented by the slope of 0.769 and Pearson r of 0.952, but some residual errors are observed. The XGMG hybrid model shows a better result where the RMSE value is 0.161, $R^2 = 0.943$, slope = 0.827, and Pearson $r = 0.971$. Its points are closely clustered about the perfect line and prediction band, showing its high accuracy and precision. The capability of real-time Drift prediction can greatly improve structural safety by issuing early warnings regarding possible failures to allow proactive interventions and design changes that are optimal for the seismic-prone regions.



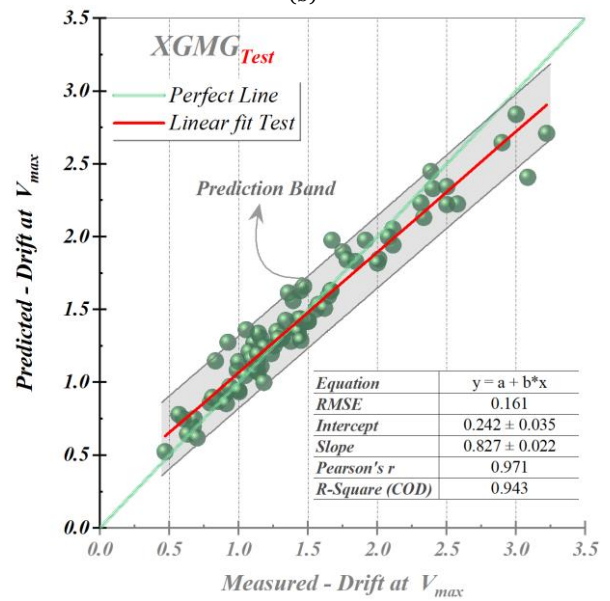
(a)



(b)



(c)



(d)

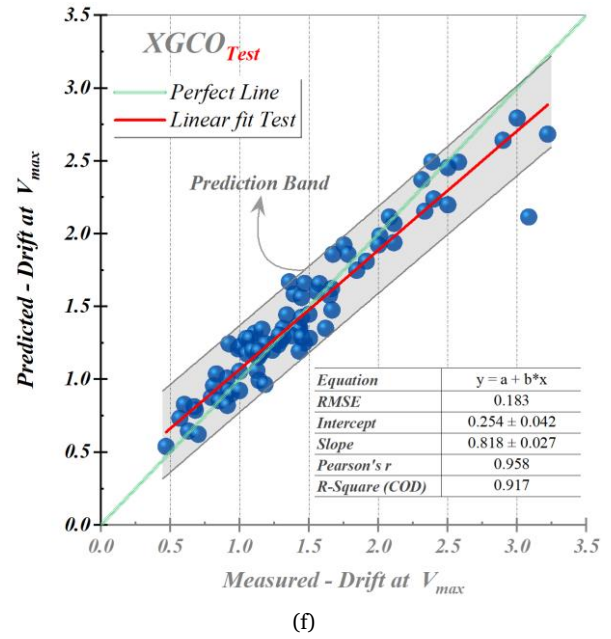
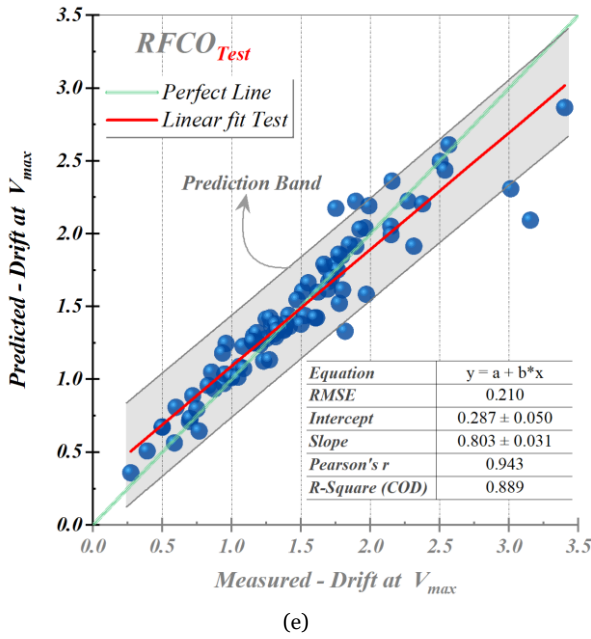


Fig. 6. The Scatter plots for correlation between the measured and predicted values in the test phase of the Drift.

Table 10 compares the measured and predicted values of Drift at the test stage, showing the performance of various models. The XGMG model has the least deviation with the measured values, as it predicts a maximum drift of 2.84, which is a -16.47% error to the measured maximum drift of 3.40 and a mean of 1.44, which is a -2.04% error to the measured mean of 1.47. Its standard deviation of 0.51 is also quite close to the observed variability of 0.61, with a 16.4 percentage

deviation. Meanwhile, the phenomenon of the RFR model is overestimated with a maximum Drift of 2.83 and indicates a greater deviation. The XGB and RFCO models offer sensible forecasts with less deviation, although they fail to represent all data dispersion as XGMG. Drift forecasting is of great importance in the prediction of the safety and stability of buildings, as well as prompting interventions and quality design in seismic regions.

Table 10. The comparison between the measured and predicted values for the test phase of Drift prediction.

Statistical Analysis	Measured	Modeling name					
		RFR	RFMG	RFCO	XGB	XGMG	XGCO
Max	3.40	2.83	2.95	2.87	2.64	2.84	2.80
Min	0.27	0.37	0.36	0.36	0.58	0.52	0.54
Mean	1.47	1.46	1.47	1.47	1.44	1.44	1.44
St. dev	0.61	0.50	0.51	0.52	0.48	0.51	0.51
Skewness	0.68	0.23	0.29	0.32	0.59	0.72	0.78

Table 11 compares the statistical error behavior of the predictive models in the Drift prediction using the test phase and shows significant differences in performance. RFR model has the highest absolute error (Max ABS), 38.61, then XGMG, with a slightly lower value of 38.14, then RFCO with an even lower value of 34.85. Even with these larger mistakes, the mean error of XGMG is 1.89 and is better than models such as XGB (2.87). Also, XGMG exhibits the least value of 11.34, indicating it is

more consistent in its predictions than RFMG, which has a standard deviation of 11.75. In spite of the fact that XGMG has the worst skew value, 1.21, which implies that it slightly under-predicts, the overall error distribution in XGMG is better than the other models. To sum up, XGMG provides a balanced and stable performance, so the company is a good candidate to apply to Drift prediction tasks.

Table 11. The statistical properties of the errors occurred in models for the test phase of Drift prediction.

Components	Properties				
	Max (ABS)	Min (ABS)	Mean	St. dev	Skewness
RFR	38.61	0.23	2.87	14.17	0.41
RFMG	36	0.05	2.71	11.75	0.57
RFCO	34.85	0.2	3.13	13.25	0.26
XGB	36.97	0.39	2.87	13.24	0.42
XGMG	38.14	0.12	1.89	11.34	1.21

The error distributions of the six models in the testing phase of Drift prediction are compared in Fig. 7 and focusing on the variability and stability of each model's predictions. The RFR model has a broad range of errors with extreme values, whereas XGMG has a smaller

range with a more concentrated distribution with lower variability. The reduced whiskers in XGMG show that it is more stable, and its IQR of -5.426 to 6.362 is narrower in comparison to the RFR of -4.796 to 8.822, showing that XGMG is more robust and predictable.

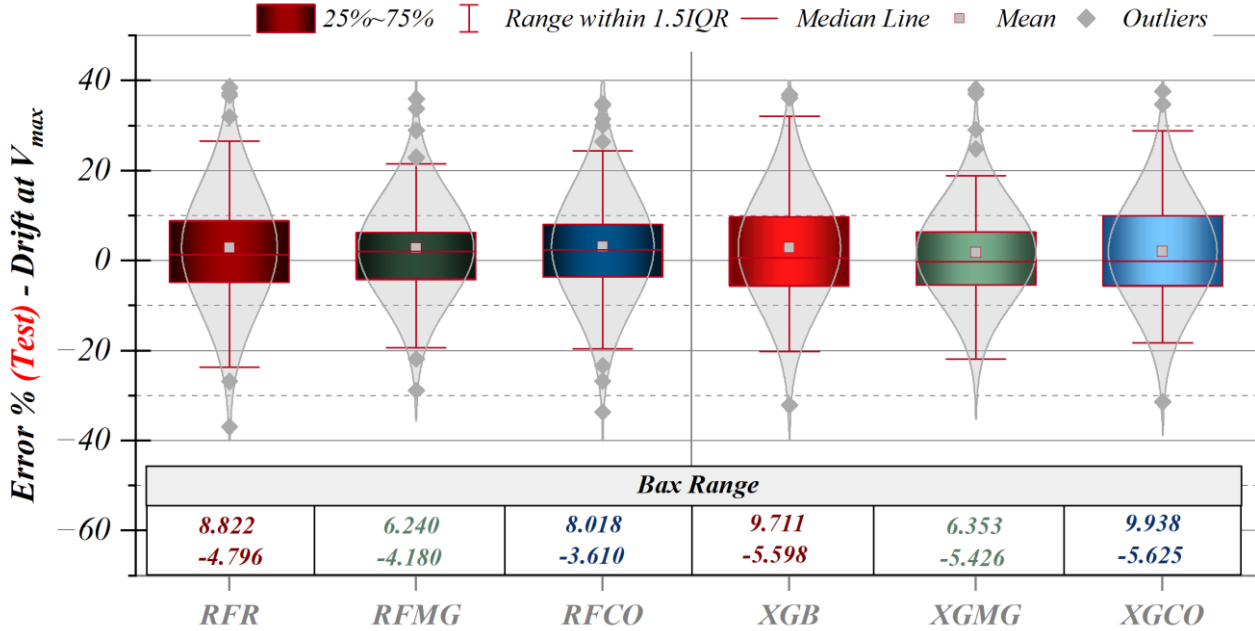


Fig. 7. The box and distribution plots for error values of the models in the test phase of Drift prediction.

5.3. Sensitivity Analysis Based on the FAST Method

FAST is an influential sensitivity analysis technique that is applied to determine the effect of model parameters on the variability of outputs when the model is repeated many times, and the domain of model runs can range from tens of thousands to hundreds of thousands. FAST employs a Fourier series representation of the model output to analyze the Fourier coefficients of the model output with the aim of estimating the expected mean output as well as the variance of the model output. The FAST technique starts with specifying the model and input parameters. After that, a unique frequency is given to each input so that the effect of each input on the output can be distinguished. A sinusoidal pattern is created for each input, and the model output is sampled at a certain point to see how it changes. FAST also employs the Fourier transformation to break down the output into frequency components, which are then used to calculate the sensitivity indices. The indices represent the extent to which each input can account for the variance in the output, and the total-order indices show the interaction between input parameters. With this systematic approach, FAST becomes a powerful instrument for finding the main factors that influence model behavior and for comprehending how these factors interact.

The FAST plots shown in Fig. 8 present the following:

- **V_{max} Prediction**

In the sensitivity analysis, the S1 values (first-order sensitivity indices) highlight the parameters that have the most direct impact on output variability. *ln* and *rousv* stand out as the most influential parameters in this regard. Conversely, the ST values (total-order sensitivity indices) account for both direct and interaction effects, revealing that Depth, *roul*, and the s/b ratio has the greatest overall influence on the output.

- **Drift Prediction**

The S1 values identify the s/b ratio and Td as the parameters with the most direct impact on output variability. In contrast, the ST values, which consider both direct and interaction effects, reveal that *ld*, Width, and *ln* have the greatest overall influence on the output.

The results of the FAST sensitivity analysis illuminate the relative influence of the input parameters on Drift and V_{max} . For example, the concrete compressive strength and the reinforcement ratio were the main factors that affected the shear capacity, while the column height and the cross-sectional dimensions were the factors that influenced the lateral drift the most. These results serve as a map for practical design: engineers can focus on the most sensitive parameters to optimize and achieve seismic performance improvement efficiently. Parameters with lower sensitivity levels may

be less stringently controlled, thus facilitating a cost-effective way of material allocation without endangering the safety. Hence, the sensitivity analysis acts as a beacon

not only for model validation but also for prudent decision-making in the design of RC columns under seismic loading.

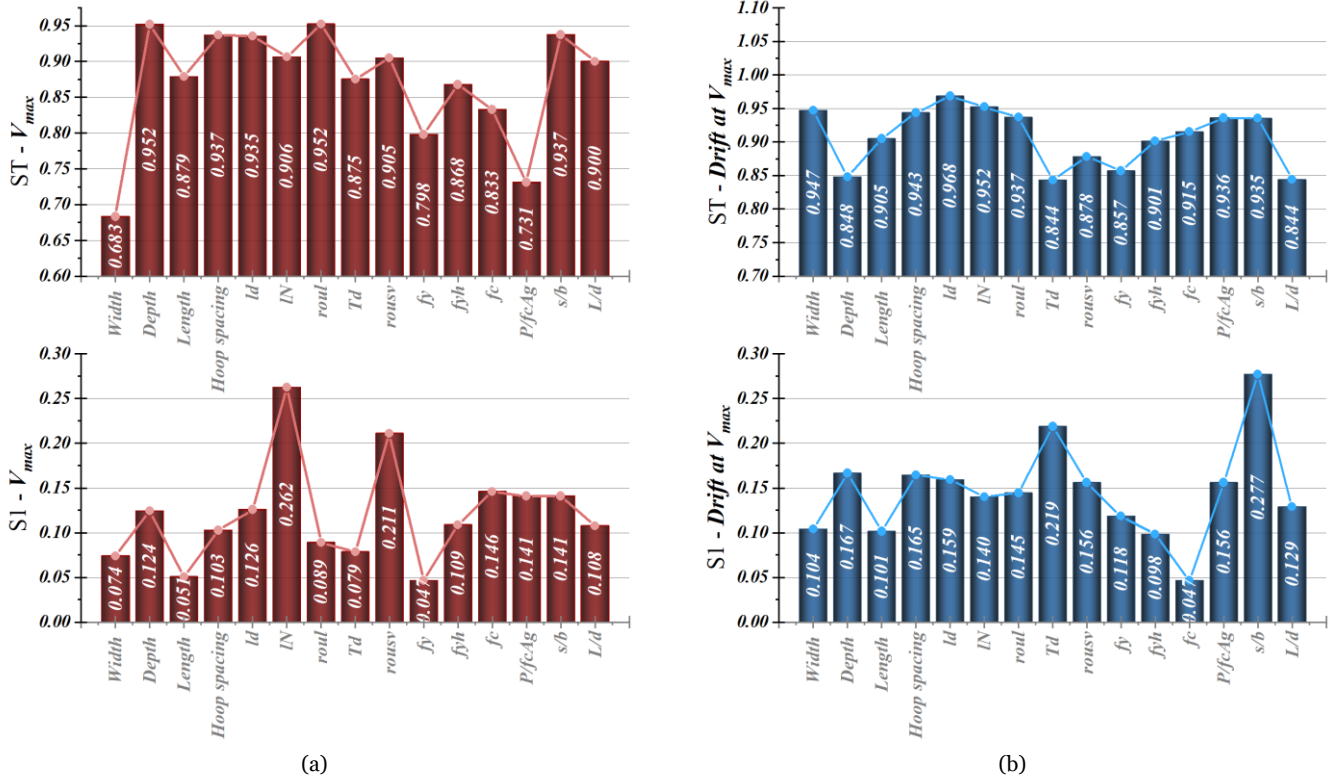


Fig. 8. The results of the FAST sensitivity analysis for determining the impact of input parameters on the V_{max} and Drift values.

6. Conclusion

This study focused on predicting the seismic performance parameters of RC columns, specifically the maximum shear strength (V_{max}) and Drift, using advanced ML models, including RFR and XGB. To enhance the performance of these models, two optimization algorithms were integrated: MGO and COA. The performance of the predictive models (RFR, RFCO, RFMG, XGB, XGCO, and XGMG) was evaluated using six key metrics: R^2 , RMSE, MNB, SI, MARE, and Theil's U (UI). Based on these evaluation results, the following conclusions can be drawn:

- For V_{max} , XGB achieved a lower RMSE of 29.908 compared to RFR's 32.239, reflecting a difference in error by approximately 7.3%. Additionally, XGB attained a higher R^2 value of 0.948, surpassing RFR's 0.936 by a margin of 1.2%. When considering hybrid models, the XGMG model exhibited the most significant improvement, reducing RMSE by 45.8% (from 29.908 to 15.810) and increasing R^2 by 3.7% (from 0.948 to 0.985) for V_{max} .
- In the case of Drift prediction, XGB also outperformed RFR, with a lower RMSE of 0.203 compared to RFR's 0.221, reflecting an 8.15% error difference. XGB's R^2 value of 0.906 was higher than RFR's 0.882 by approximately

2.4%. The XGMG model again demonstrated superior performance, reducing RMSE by 20.6% (from 0.203 to 0.161) and increasing R^2 by 3.9% (from 0.906 to 0.943) for Drift. These comparisons highlight the substantial improvements provided by the hybrid models, particularly XGMG, in both V_{max} and Drift predictions.

- Sensitivity analysis using FAST plots revealed key parameters influencing the output variability. For V_{max} , lN and $rousv$ were identified as the most impactful parameters in terms of direct effects, while $Depth$, $roul$, and the s/b ratio were shown to influence the output when considering both direct and interaction effects. For Drift, the s/b ratio and Td were the most significant direct parameters, with ld , $Width$, and lN playing an important role in the overall prediction.

The study results highlight how ML methods, especially the XGMG hybrid model, can be powerful tools to provide accurate and consistent predictions of seismic performance parameters. The revelations are quite significant for structural engineers since they will help them make decisions for the design, retrofitting, and safety assessment of RC structures in seismic regions, which is the core of the evolution towards more resilient and efficient infrastructures. The suggested models are

those that can be utilized in the everyday engineering work processes to quickly and reliably achieve the seismic performance of RC columns. By the engineer's design software or spreadsheets, it is possible to calculate Drift and V_{max} with minimal experimental testing and without a detailed FEA. Moreover, the models combined with sensitivity insights can be very useful in making design decisions based on seismic design codes, which guarantee safety and economic efficiency in a real-life situation.

Conflicts of Interests

There is no conflict of interest in this study.

Funding

Self-funded.

Acknowledgments

Not applicable.

Availability of Data and Materials

The datasets used during the current study are available from the corresponding author on request.

Using Artificial Intelligent Chatbots

None.

References

- [1] Naeim B, Khiavi AJ, Dolatimehr P, Sadaghat B. Novel Optimized Support Vector Regression Networks for Estimating Fresh and Hardened Characteristics of SCC 2024.
- [2] Code P. Eurocode 8: Design of structures for earthquake resistance—Part 3: Assessment and retrofitting of buildings. Incorporating Corrigendum March 2010.
- [3] Khajavi E, Taghavi Khanghah AR, Javadzade Khiavi A. An efficient prediction of punching shear strength in reinforced concrete slabs through boosting methods and metaheuristic algorithms. *Structures* 2025;74:108519. doi:<https://doi.org/10.1016/j.istruc.2025.108519>
- [4] Priestley MJN, Verma R, Xiao Y. Seismic shear strength of reinforced concrete columns. *Journal of Structural Engineering* 1994;120:2310–29.
- [5] Sezen H, Moehle JP. Shear strength model for lightly reinforced concrete columns. *Journal of Structural Engineering* 2004;130:1692–703.
- [6] Elwood KJ, Moehle JP. Drift capacity of reinforced concrete columns with light transverse reinforcement. *Earthquake Spectra* 2005;21:71–89.
- [7] Moretti M, Tassios TP. Behaviour of short columns subjected to cyclic shear displacements: Experimental results. *Engineering Structures* 2007;29:2018–29.
- [8] Taheri A, Moghadam AS, Tasnimi AA. Critical factors in displacement ductility assessment of high-strength concrete columns. *International Journal of Advanced Structural Engineering* 2017;9:325–40.
- [9] Kabeyasawa T. DEFORMATION CAPACITY OF REINFORCED CONCRETE. *ACI Structural Journal* 2009;106:187–95.
- [10] Wibowo A, Wilson JL, Lam NTK, Gad EF. Drift capacity of lightly reinforced concrete columns. *Australian Journal of Structural Engineering* 2014;15:131–50.
- [11] Ferdous W, Manalo A, Aravinthan T, Fam A. Flexural and shear behaviour of layered sandwich beams. *Construction and Building Materials* 2018;173:429–42.
- [12] Jahangiri V, Akbarzadeh MR, Shahamat SA, Asgari A, Naeim B, Ranjbar F. Machine learning-based prediction of seismic response of steel diagrid systems. *Structures*, vol. 80, Elsevier; 2025, p. 109791.
- [13] Kim S-H, Han S-J, Kim KS. Nonlinear finite element analysis formulation for shear in reinforced concrete beams. *Applied Sciences* 2019;9:3503.
- [14] Naeim B, Akbarzadeh MR, Jahangiri V. Machine learning-based prediction of seismic response of elevated steel tanks. *Structures* 2024;70:107649. doi:<https://doi.org/10.1016/j.istruc.2024.107649>
- [15] Lucchini A, Franchin P, Kunnath S. Failure simulation of shear-critical RC columns with non-ductile detailing under lateral load. *Earthquake Engineering & Structural Dynamics* 2017;46:855–74.
- [16] Lu X, Ye L, Pan P, Zhao Z, Ji X, Qian J. Pseudo-static collapse experiments and numerical prediction competition of RC frame structure I: RC frame experiment. *Building Structure* 2012;42:19–22.
- [17] Ibarra LF, Medina RA, Krawinkler H. Hysteretic models that incorporate strength and stiffness deterioration. *Earthquake Engineering & Structural Dynamics* 2005;34:1489–511.
- [18] Haselton CB, Liel AB, Deierlein GG. Simulating structural collapse due to earthquakes: model idealization, model calibration, and numerical solution algorithms. *Computational Methods in Structural Dynamics and Earthquake Engineering (COMPdyn)* 2009.
- [19] Liel AB, Haselton CB, Deierlein GG. Seismic collapse safety of reinforced concrete buildings. II: Comparative assessment of nonductile and ductile moment frames. *Journal of Structural Engineering* 2011;137:492–502.
- [20] Lucchi E. Non-invasive method for investigating energy and environmental performances in existing buildings. *Proceedings of the PLEA Conference on Passive and Low Energy Architecture*, Louvain-la-Neuve, Belgium, 2011, p. 13–5.
- [21] Sadaghat B, Ebrahimi SA, Souri O, Yahyavi Niar M, Akbarzadeh MR. Evaluating strength properties of Eco-friendly Seashell-Containing

- Concrete: Comparative analysis of hybrid and ensemble boosting methods based on environmental effects of seashell usage. *Eng Appl Artif Intell* 2024;133:108388. doi:doi.org/10.1016/j.engappai.2024.108388.
- [22] Dang B-L, Doan LT, Van Hai N, Phan DN, Nguyen-Xuan H, Dang VQ. Effect of Curing Conditions on the Mechanical Properties and Permeability of Concrete Incorporating Sulfate-Resistant Admixture BT - Recent Advances in Structural Health Monitoring and Engineering Structures. In: Cuong LT, Gandomi AH, Abualigah L, Khatir S, editors., Singapore: Springer Nature Singapore; 2024, p. 619–28.
- [23] Peng Y, Unluer C. Modeling the mechanical properties of recycled aggregate concrete using hybrid machine learning algorithms. *Resources, Conservation and Recycling* 2023;190:106812. doi:https://doi.org/10.1016/j.resconrec.2022.106812.
- [24] Benito EKD, Aragoncillo AMM, Pascua FAA, Juanites JM, Eneria MA, Zafra RG, Madlangbayan MS. Durability performance of concrete containing recycled coarse aggregates derived from laboratory-tested specimens. *World Journal of Engineering* 2023.
- [25] Hameed MM, Abed MA, Al-Ansari N, Alomar MK. Predicting compressive strength of concrete containing industrial waste materials: novel and hybrid machine learning model. *Advances in Civil Engineering* 2022;2022:1–19.
- [26] Huang J, Zhou M, Yuan H, Sabri MM, Li X. Prediction of the Compressive Strength for Cement-Based Materials with Metakaolin Based on the Hybrid Machine Learning Method. *Materials* 2022;15. doi:10.3390/ma15103500.
- [27] Tavana Amlashi A, Mohammadi Golafshani E, Ebrahimi SA, Behnood A. Estimation of the compressive strength of green concretes containing rice husk ash: a comparison of different machine learning approaches. *European Journal of Environmental and Civil Engineering* 2023;27:961–83. doi:10.1080/19648189.2022.2068657.
- [28] Khatti J, Grover KS. Prediction of UCS of fine-grained soil based on machine learning part 2: comparison between hybrid relevance vector machine and Gaussian process regression. *Multiscale and Multidisciplinary Modeling, Experiments and Design* 2023. doi:10.1007/s41939-023-00191-8.
- [29] Khatti J, Grover KS. A Scientometrics Review of Soil Properties Prediction Using Soft Computing Approaches. *Archives of Computational Methods in Engineering* 2024;31:1519–53. doi:10.1007/s11831-023-10024-z.
- [30] Sathyapriya S, Arumairaj PD, Ranjini D. Prediction of unconfined compressive strength of a stabilised expansive clay soil using ANN and regression analysis (SPSS). *Asian J Res Soc Sci Humanit* 2017;7:109–23.
- [31] Oreta AWC, Kawashima K. Neural network modeling of confined compressive strength and strain of circular concrete columns. *Journal of Structural Engineering* 2003;129:554–61.
- [32] Peruš I, Poljanšek K, Fajfar P. Flexural deformation capacity of rectangular RC columns determined by the CAE method. *Earthquake Engineering & Structural Dynamics* 2006;35:1453–70.
- [33] Chou J-S, Ngo N-T, Pham A-D. Shear strength prediction in reinforced concrete deep beams using nature-inspired metaheuristic support vector regression. *Journal of Computing in Civil Engineering* 2016;30:4015002.
- [34] González MP, Zapico JL. Seismic damage identification in buildings using neural networks and modal data. *Computers & Structures* 2008;86:416–26.
- [35] Reza SM, Alam MS, Tesfamariam S. Lateral load resistance of bridge piers under flexure and shear using factorial analysis. *Engineering Structures* 2014;59:821–35.
- [36] Zhu L, Qiu D, Ergu D, Ying C, Liu K. A study on predicting loan default based on the random forest algorithm. *Procedia Computer Science* 2019;162:503–13.
- [37] Naruei I, Keynia F. A new optimization method based on COOT bird natural life model. *Expert Systems with Applications* 2021;183:115352.
- [38] Abdollahzadeh B, Gharehchopogh FS, Khodadadi N, Mirjalili S. Mountain gazelle optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems. *Advances in Engineering Software* 2022;174:103282. doi:doi.org/10.1016/j.advengsoft.2022.103282.
- [39] Liu Z, Li S. Development of an ANN-based lumped plasticity model of RC columns using historical pseudo-static cyclic test data. *Applied Sciences* 2019;9:4263.
- [40] Browning, J.A.; Pujol, S.; Eigenmann, R.; Ramirez JA. NEEShub Databases. *Concrete International* 2013;35.
- [41] Washington. U of. The UW-PEER Reinforced Concrete Column Test Database. University of Washington 2004.
- [42] Singh G, Panda RK. Daily sediment yield modeling with artificial neural network using 10-fold cross validation method: a small agricultural watershed, Kapgari, India. *Int J Earth Sci Eng* 2011;4:443–50.
- [43] Li H. Reliable Hybridization Approach for Estimation of The Heating Load of Residential Buildings. *International Journal of Advanced Computer Science & Applications* 2024;15.
- [44] Scott E, Graham A. A comparative study of hybrid adaptive neuro-fuzzy inference systems to predict the unconfined compressive strength of rocks. *Advances in Engineering and Intelligence Systems* 2024;3:1–17.