Fusion Journal of Engineering and Sciences

Article

Application of the Gradient Boosting Algorithm for Bond Strength Prediction of GFRP bars with Concrete

Muhammad Saad Ifrahim[1,*], Dr. Abdul Jabbar Sangi [2], Dr. Fawwad Masood [2], and Muhammad Umer Bin Abid Bhatti[4]

[1] Lecturer, Department of Civil Engineering, NED University of Engineering and Technology, Pakistan; msaadifrahim@cloud.neduet.edu.pk
[2] Professor and Chairperson, Department of Civil Engineering, NED University of Engineering and Technology, Pakistan; ajsangi@cloud.neduet.edu.pk
[3] Assistant Professor, Department of Civil Engineering, NED University of Engineering and Technology, Pakistan; fawwad@cloud.neduet.edu.pk
[4] Design Engineer, MZB Engineering Inc, United States; umerabid564@gmail.com
* Correspondence: msaadifrahim@cloud.neduet.edu.pk

Abstract

In marine environment, chloride-induced rebar corrosion is the principal cause of reinforced concrete degradation, resulting in material loss, cracking, and bond failure, all of which dramatically degrade structural safety, load-bearing capacity, and service life. As a result, using non-corrosive reinforcement, such as Glass Fibre Reinforced Polymer (GFRP) bars, is critical for increasing the service life of structures exposed to marine environments. It has a variety of other benefits over steel rebar as well, including, higher tensile strength, cost-effectiveness, reduced density, and non-magnetic property. The bond behaviour of GFRP bars with concrete differs from that of steel, as it exhibits linearly elastic behaviour with a distinct surface deformation pattern. While several empirical models exist to estimate bond strength, their predictive accuracy is limited; therefore, it is imperative to develop a more robust, data-driven prediction model. This study demonstrates the effectiveness of Gradient Boosting-based Machine Learning model, optimized via Optuna with K-fold cross-validation, on estimating the bond strength of GFRP bars with concrete. Analysis of the results indicates that the model yields superior performance metrics across both the training and testing phases, characterized by a higher coefficient of determination (R^2) and a reduced Root Mean Square Error (RMSE). As a result, it may be inferred that the model has a higher predictive capacity than empirical equations.

Keywords: GFRP bars; concrete bond strength; fiber reinforced polymer; machine learning; Gradient Boosting; data-driven modeling; hyperparameter optimization

1. Introduction

Corrosion of steel reinforcement is a key driver of structural failure in reinforced concrete; therefore, represents a major engineering obstacle. The mechanical properties of steel reinforcement deteriorate due to corrosion caused by chloride ions (from de-icing substances or the marine environment) penetrating reinforced concrete [1,2]. Therefore, there is a need for alternative reinforcement that can solve this problem. One of the possible solutions is the adoption of nonmetallic reinforcement known as Fibre Reinforced Polymer (FRP) bars [3]. These bars come with different fibres, such as glass, carbon, aramid, and basalt. Among these, Glass Fibre reinforced polymer (GFRP) bars are the most promising in terms of strength and cost. These bars are non-corrosive in nature, so they permanently address the concern of corrosion in reinforced concrete. Furthermore, it offers higher tensile strength, lower density, and non-magnetic properties [3,4]. The bond of GFRP bars with concrete is different from that of steel bars due to their linearly elastic behavior and distinct surface deformation patterns, such as helical wrapping and sand coating. Scholarly investigations frequently demonstrate that GFRP reinforcement possesses weaker bonding characteristics with concrete when compared to standard steel rebar. There are number of empirical equations (e.g. ACI 4401. R15 [5], CSA S806-12 [6], Lee et al. [7]) available in the literature that can predict bond strength of GFRP bars. Shahri and Mousavi [8] and Huang et al. [9] reported that existing empirical expressions fail to reliably estimate the bond strength of GFRP bars embedded in concrete. Similarly, Saad et al. [10] noted that neither conventional nor modern bond models explicitly incorporate the influence of varying parameters, underscoring the necessity for more advanced models that can predict bond behavior without relying on experimental calibration. This reveals a research gap: there is a need for advanced predictive frameworks to accurately estimate the bond strength of GFRP bars with concrete. The data-driven machine learning approach is promising, as it can capture complex nonlinear relationships between the parameters. Moreover, as per the comprehensive review by Yue et al. [11], the integration of machine learning into FRP-reinforced concrete is an emerging research area. Therefore, this work seeks to create a data-driven machine learning model utilizing the Gradient Boosting algorithm to estimate the bond strength of GFRP bars with concrete, achieving more accuracy than empirical models.

2. Dataset compilation

A dataset of 505 data points regarding GFRP-to-concrete bond behavior is synthesized by conducting a systematic review of existing literature [12–24]. This dataset is utilized to evaluate the performance of existing empirical equations against a machine learning model based on the Gradient Boosting algorithm. Key features included in the dataset are bar diameter, development length, concrete strength, concrete cover, and surface treatment (sand-coated vs. non-coated). The reported bond strength values in existing literature vary widely, ranging from 2.5 to 35.3 MPa with a coefficient of variation of 54%. Such a broad spectrum and high degree of variability indicate the significant impact of multiple interacting factors and a lack of uniformity in testing procedures across different studies. Consequently, this compiled database provides a comprehensive overview of reported bond performance while emphasizing the necessity of developing predictive models that can more accurately account for such inherent variability.

3. Assessment of empirical equations

In order to predict the bond strength of FRP bars with concrete, several empirical equations are available in the literature, including those from ACI 440.1R-15 [5] and Lee et al [7]. These two empirical models were evaluated against the developed dataset (see Table 1 and Figure 1). It was found that both exhibited substantially lower coefficients of determination and higher root mean-square errors. Similar conclusions have been reported for these and other empirical equations in previous studies. This discrepancy in performance underscores the necessity for more advanced, data-driven predictive frameworks that can directly capture the nonlinear relationships present in experimental data.

Table 1. Summary of performance metrics for empirical models

Performance Indicators	ACI 440.1 R15	Lee et al.
R2	0.18	0.17
RMSE	7.04	6.51

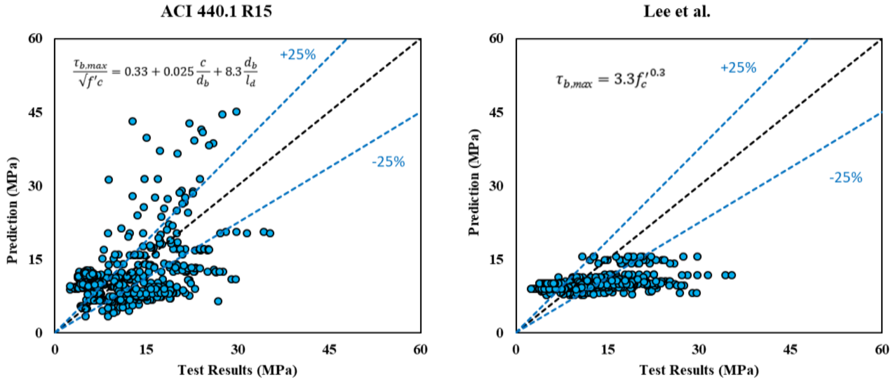

Figure 1. Assessment of ACI 440.1R-15 and Lee et al. empirical equations using the developed dataset

4. Development of Machine Learning model

The predictive framework was constructed using the Gradient Boosting algorithm within the Python environment. As detailed in Figure 2, this ensemble method [25] generates a robust predictor by sequentially amalgamating multiple 'weak' learners, predominantly decision trees. The defining characteristic of this approach is its error-correction mechanism: rather than training models in isolation, each subsequent tree attempts to reduce the errors left by its predecessor. By employing gradient descent to optimize a loss function, the algorithm trains new learners on the residuals of the loss function relative to the previous prediction. The ultimate prediction is an accumulation of these incremental corrections, expressed mathematically as:

$$y_{pred} = y_1 + \sum_{i=1}^{N} \eta \ .r_i$$

Where y_1 is the initial baseline prediction, r_i is the error predicted by the $i-th$ tree, and η (learning rate) is a shrinkage parameter that scales each tree's contribution to prevent overfitting.

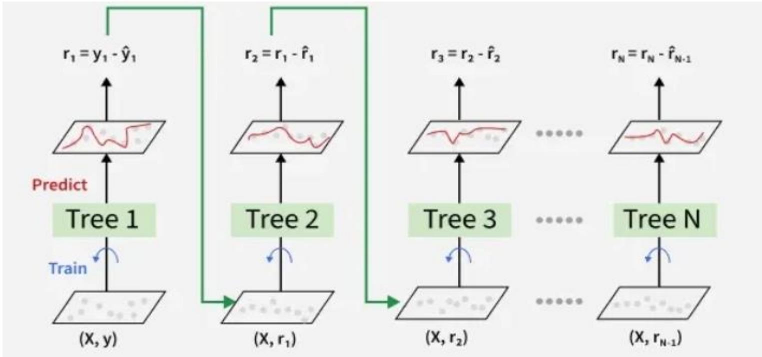

Figure 2. Schematics of Gradient Boosting algorithm [25]

Hyperparameters control the model's complexity and learning process to prevent overfitting and ensure accurate predictions on unseen data. Therefore, the hyperparameters of the gradient boosting algorithm must be optimized for the specific dataset. To achieve this, the approach shown in Figure 3 is adopted, where Optuna optimization is used alongside K-fold cross-validation at every iteration (100 iterations, 7 folds). This ensures the development of a robust model that prioritizes generalization over learning noise. Table 2 shows the optimized set of hyperparameters used in this study.

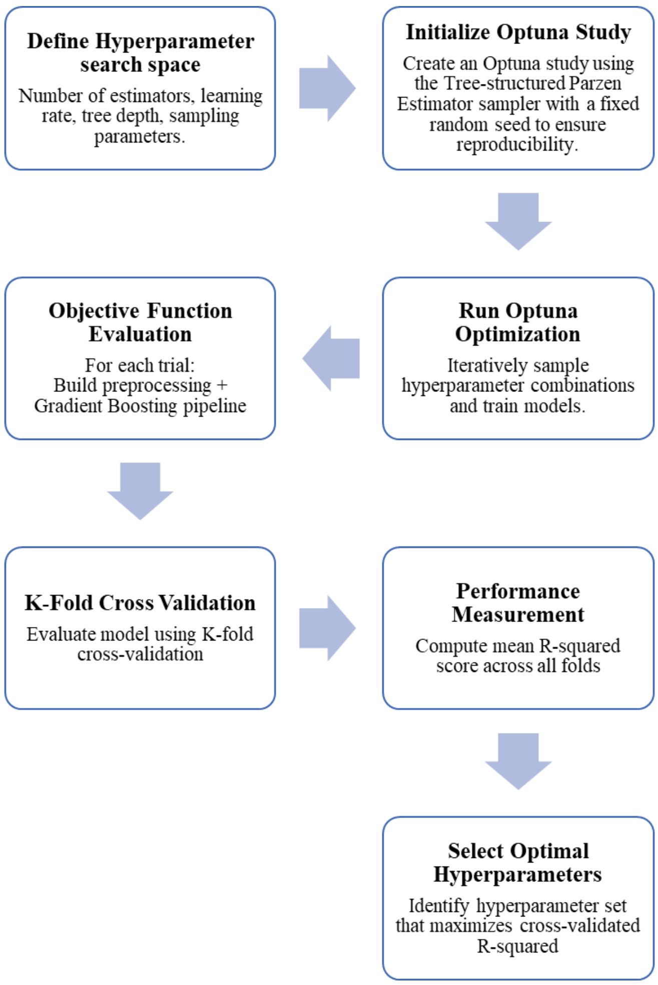

Figure 3. Schematic representation of the hyperparameter optimization framework utilizing the Optuna automated tuning library with K-Fold Cross-Validation for the Gradient Boosting regression model.

Table 2. Optimized hyperparameters for the Gradient Boosting model.

Hyperparameter	Value
Number of Estimators	348
Learning Rate	0.05
Maximum Depth	4
Minimum Samples per Leaf	3
Minimum Samples Split	3
Maximum Features	Logarithmic (log2)
Subsample Ratio	0.79

In machine learning model development, standard practice involves partitioning the dataset into a training set for model training and a testing set for performance evaluation. In this study, the data was divided using a 70/30 split, with 70% allocated for training and 30% for testing. The results presented in Table 3 and Figure 4 demonstrate that the Gradient Boosting algorithm achieves superior accuracy compared to the empirical equations. Specifically, the model exhibits a higher coefficient of determination (R^2) and a lower Root Mean Square Error (RMSE), underscoring its strong predictive capability for the bond strength of GFRP bars. Furthermore, the Goodness-of-Fit Assessment (as shown in Figure 5) reveals a normal distribution centered at zero, indicating that the Gradient Boosting model is unbiased and that the prediction errors are random rather than systematic. It should also be noticed that the testing dataset shows a decrease in R^2 and an increase in RMSE compared to the training phase. This disparity suggests that while the current model is effective, further investigation into alternative algorithms could potentially yield even better generalization results.

Table 3. Performance of the Machine Learning Model

Performance Indicators	Gradient Boosting Model (Training dataset)	Gradient Boosting Model (Testing dataset)	Gradient Boosting Model (Complete dataset)
R2	0.90	0.81	0.87
RMSE	2.00	3.06	2.37

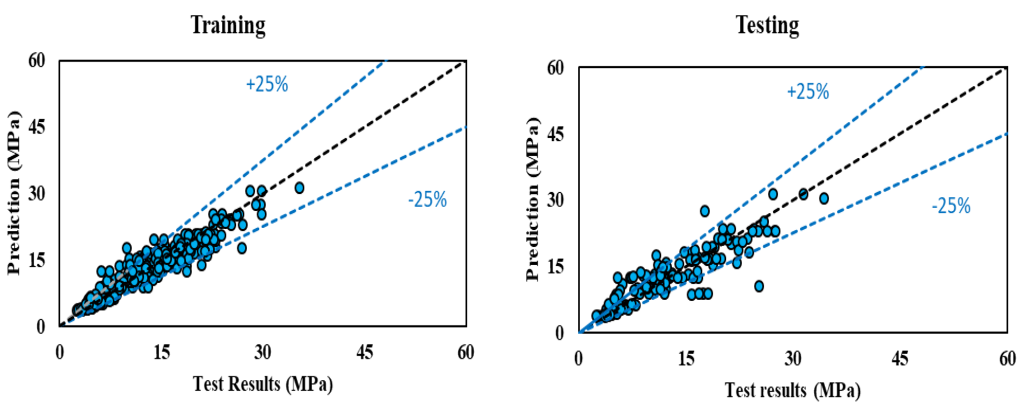

Figure 4. Assessment of the developed model's predictive accuracy against experimental data

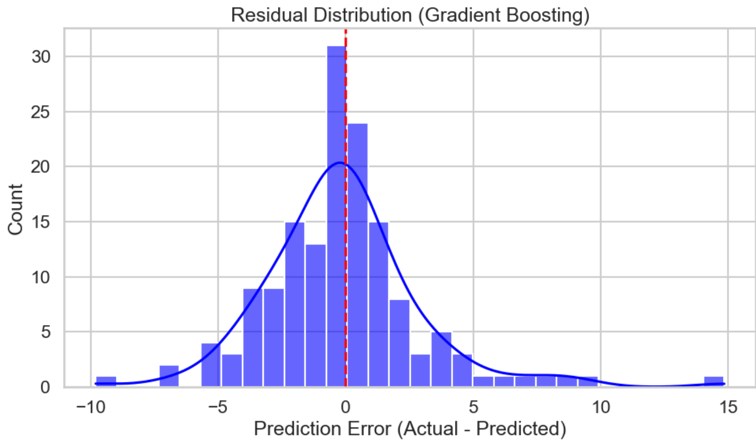

Figure 5: Goodness-of-Fit assessment for the ML model

5. Conclusions

On the basis of above study, following conclusions are formulated:

1. Statistical analysis reveals that the empirical formulas from ACI 440.1R-15 [5] and Lee et al. [7] failed to provide precise estimates of GFRP bond strength for the collected dataset. The models exhibited substantial deficiencies, evidenced by low coefficients of determination (R2) and high Root Mean Square Error (RMSE) values. This finding is consistent with previous studies [8–9].
2. The developed machine learning model based on Gradient Boosting algorithm, trained with Optuna hyperparameter optimization incorporating K-fold cross-validation, demonstrated superior predictive accuracy for estimating the bond strength of GFRP bars with concrete. The developed model outperformed existing empirical formulas, yielding improved statistical metrics, specifically a higher R^2 value alongside a lower RMSE.
3. The observed marginal discrepancy between the training and testing results points to the possibility of mild overfitting within the model. Therefore, the model's generalization should be further validated using independent datasets. Future work could explore alternative machine learning algorithms, such as Random Forest, XGBoost, and AdaBoost, with Optuna optimization and K-fold cross-validation.

Author Contributions: Conceptualization, M.S.I and A.J.S.; methodology, M.S.I and M.U.B.A,B,; software, M.S.I and M.U.B.A.B.; validation, M.S.I, A.J.S., and F.M..; formal analysis, M.S.I; investigation, M.S.I; resources, A.J.S.; data curation, M.S.I; writing original draft preparation, M.S.I; writing review and editing, A.J.S. and F.M.; visualization, M.S.I; supervision, M.S.I; project administration, M.S.I; funding acquisition, A.J.S.. The final version of the manuscript has been reviewed and approved by all listed authors.

Acknowledgments: The authors express their gratefulness to Sindh HEC for funding this work under the Sindh Research Support Program. Additionally, the authors would like to thank Muhammad Khizr, Afifa Zain, and Mahad Ali Siddiqui, final-year design project students, for their support with preliminary data collecting and literature organization. During the preparation of this manuscript, the author(s) utilized QuillBot and Gemini for the purposes of paraphrasing and improving grammatical accuracy. The authors assume full accountability for the integrity of this work, having thoroughly verified and refined the final content.

Conflicts of Interest: The authors report no competing interests regarding the publication of this paper.

References

[1] Gibson FW. Corrosion, concrete, and chlorides: steel corrosion in concrete: causes and restraints, American Concrete Institute; 1987.

[2] Ahmad S. Reinforcement corrosion in concrete structures, its monitoring and service life prediction - A review. Cem Concr Compos 2003;25:459–71. https://doi.org/10.1016/S0958-9465(02)00086-0.

[3] Lorenzis L De, Nanni A. An Introduction to FRP Composites for Construction. ACI Struct J 2002.

[4] Zadeh HJ, Nanni A. Design of RC columns using glass FRP reinforcement. Journal of Composites for Construction 2013;17:294–304.

[5] ACI 440.1 R-15. Guide for the design and construction of structural concrete reinforced with FRP bars. Farmington Hills, MI: American Concrete Institute; 2015.

[6] CSA S806-12. Design and construction of building structures with fibre-reinforced polymers. Toronto: Canadian Standards Association; 2012.

[7] Lee J-Y, Kim T-Y, Kim T-J, Yi C-K, Park J-S, You Y-C, et al. Interfacial bond strength of glass fiber reinforced polymer bars in high-strength concrete. Compos B Eng 2008;39:258–70.

[8] Farahi Shahri S, Mousavi SR. Predicting the bond strength between concrete and glass fiber-reinforced polymer bars using soft computing models. Iranian Journal of Science and Technology, Transactions of Civil Engineering 2023;47:3507–22.

[9] Huang T, Wan C, Liu T, Hao D, Miao C. Machine learning prediction method for the interface bond strength between fiber reinforced polymer bars and concrete based on multi-feature driven analysis. Mater Today Commun 2024;41:110706.

[10] Saad S, Polak MA. Bond behavior of glass fiber-reinforced polymer (GFRP) bars embedded in concrete: a review. Materials 2025;18:3367.

[11] Yue Z, Ouyang K, Yao X, Hu K, Li L. A critical review of fiber reinforced polymer bars: a scientometric and visualization analysis. Cleaner Materials 2025:100325.

[12] Ifrahim MS, Sangi AJ, Hamza SM. Experimental Study on Bond Strength of Locally Manufactured GFRP Bar. Engineering Proceedings 2022;22:4.

[13] Basaran B, Kalkan I. Investigation on variables affecting bond strength between FRP reinforcing bar and concrete by modified hinged beam tests. Compos Struct 2020;242:112185.

[14] Guo Y-C, Cai Y-J, Xie Z-H, Xiao S-H, Zhuo K-X, Cai P-D, et al. Experimental investigation of GFRP bar bonding in geopolymer concrete using hinged beam tests. Eng Struct 2025;322:119036.

[15] Hossain KMA, Ametrano D, Lachemi M. Bond strength of GFRP bars in ultra-high strength concrete using RILEM beam tests. Journal of Building Engineering 2017;10:69–79.

[16] Cosenza E, Manfredi G, Pecce M, Realfonzo R. Bond between glass fiber reinforced plastic reinforcing bars and concrete—Experimental analysis. Special Publication 1999;188:347–58.

[17] Kachlakev DI. Experimental and analytical study on unidirectional and off-axis GFRP rebars in concrete. Compos B Eng 2000;31:569–75.

[18] Szczech D, Kotynia R. Beam bond tests of GFRP and steel reinforcement to concrete. Archives of Civil Engineering 2018;64:243–56.

[19] Sólyom S, Balázs G. GFRP reinforcement for concrete structures -study of the effect of surface profile on bond behavior. 2018.

[20] Qader ZM, Kakshar FSM. Experimental Investigation on Bond Stress Behavior of Sand-Coated GFRP Bars with Concrete. Zanco J Pure Appl Sci 2023;35:30–8.

[21] Rather AI, Banerjee S, Laskar A. Effect of bar surface geometry on bond behavior in GFRP-reinforced concrete beams: Experiments and design implications. Journal of Composites for Construction 2024;28:04024072.

[22] Okelo R, Yuan RL. Bond strength of fiber reinforced polymer rebars in normal strength concrete. Journal of Composites for Construction 2005;9:203–13.

[23] Tighiouart B, Benmokrane B, Gao D. Investigation of bond in concrete member with fibre reinforced polymer (FRP) bars. Constr Build Mater 1998;12:453–62.

[24] Köroğlu MA. Artificial neural network for predicting the flexural bond strength of FRP bars in concrete. Science and Engineering of Composite Materials 2019;26:12–29.

[25] GeeksforGeeks. Gradient Boosting in ML 2025.