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Strength Prediction of CFST Columns Confined with CFRP using Machine Learning Techniques

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A B S T R A C T

Concrete-filled steel tube columns confined with carbon fiber reinforced polymer have thus been proved to be significant in increasing the load-carrying capacity and ductility of structural elements, ideal for modern high-performance structure applications. Traditional methods in predicting strength for CFST columns confined with CFRP are quite complex, time-consuming, and rely more on empirical formulas that do not tend to be very general. Based on these limitations, this research aims to study whether machine learning could predict compressive strength in CFRP-confined CFST columns. In this study, ML was trained using a well-comprehensive dataset of properties, geometric parameters, and confinement characteristics on various different models, including linear regression, decision trees, more advanced algorithms such as SVM and ANN. The following is the testing for every model: prediction accuracy and the root mean square error while correlated with strength values attained experimentally. The results show that the performance of machine learning models far exceeds that of traditional predictive formulas in terms of higher accuracy and adaptability in the most diverse CFST column configurations. Further, it was shown in the analysis that ML models have a strong potential for generalizing through different confinement levels, dimensions of the column, and material properties, and is hence a more reliable tool in hand for an engineer to calculate column strength. This approach not only improves the accuracy of strength prediction but also contributes to optimizing the design of CFST structures, hence supporting the more widespread use of CFRP in structural engineering applications.

Keywords: Concrete-Filled steel tube (CFST) column, Cabon fibre Reinforced polymer (CFRP), Compressive Strength Prediction, Machine Learning, Prediction Accuracy, structural engineering applications

INTRODUCTION

CFST (Concrete-Filled Steel Tube)

Concrete-Filled Steel Tube (CFST) columns are composite structural elements that combine the strength of steel and concrete to form a highly efficient load-bearing component. In CFST columns, a hollow steel tube is filled with concrete, leveraging the benefits of both materials. The steel tube provides a formwork for the concrete during construction and acts as a permanent reinforcement, enhancing the column's load-carrying capacity and ductility. The concrete, on the other hand, prevents local buckling of the steel tube and improves its overall stability and stiffness. This synergy between steel and concrete allows CFST columns to perform exceptionally well under various loading conditions, making them ideal for use in high-rise buildings, bridges, and other critical infrastructure. CFST columns offer several advantages, including improved construction efficiency and cost-effectiveness. Since the steel tube serves as a formwork, it eliminates the need for additional formwork, reducing construction time and labor costs. Additionally, CFST columns exhibit excellent fire resistance, as the concrete core protects the steel from high temperatures. The composite action of the materials also results in better seismic performance, making CFST columns suitable for use in earthquake-prone areas. Furthermore, their aesthetic appeal and structural versatility have made CFST columns a popular choice in modern architectural and engineering applications.

CFRP (Carbon Fiber Reinforced Polymer):

CFRP stands for Carbon Fiber Reinforced Polymer, which is a composite material widely used in various engineering applications due to its exceptional strength-to-weight ratio and durability. CFRP is composed of carbon fibers, typically in the form of woven fabric or mats, embedded in a polymer resin matrix. The carbon fibers provide high tensile strength and stiffness, while the polymer resin matrix enhances toughness and durability.

In CFRP, the carbon fibers are aligned in a specific orientation to optimize the material's mechanical properties based on the application's requirements. The composite's performance is influenced by factors such as fiber volume fraction, fiber orientation, resin type, and manufacturing process. CFRP finds extensive use in aerospace, automotive, marine, civil engineering, and sports equipment industries, where lightweight and high-strength materials are crucial for enhancing performance, reducing fuel consumption, and improving structural integrity. Its applications range from aircraft fuselages and automotive components to reinforcement of concrete structures and sporting goods like tennis rackets and bicycles.

Literature Review

- Concrete-Filled Steel Tube (CFST) columns use concrete inside steel tubes to achieve high strength and durability, while Carbon Fiber Reinforced Polymer (CFRP) confinement further enhances their strength and ductility, making them suitable for robust infrastructure.
- CFRP confinement improves the performance of CFST columns by providing lateral support, which increases compressive strength and ductility, both essential for structural resilience under heavy loads.
- Traditional methods like empirical formulas and analytical models lack the precision needed to capture the complex interactions in CFRP-confined CFST columns.
- Machine Learning (ML) techniques, such as neural networks and regression models, can handle complex, nonlinear relationships and process large datasets, improving the accuracy of strength predictions for CFRP-confined CFST columns.
- ML models use data from experiments with varied CFRP configurations, concrete strengths, and column dimensions to train and validate predictions, ensuring accuracy.
- Researchers apply ML to integrate diverse features, like CFRP and concrete properties, to predict the strength improvements achieved in CFST columns with CFRP confinement.
- ML model predictions are validated against experimental data using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), often outperforming traditional methods.
- Sensitivity analysis identifies key parameters, such as CFRP wrapping orientation and concrete strength, that significantly impact CFST column strength, aiding in design optimization.
- ML models are applied in real-world projects for designing and retrofitting CFST columns with CFRP, improving structural resilience and extending service life.
- Despite its effectiveness, ML faces challenges in data quality and complexity. Future research includes incorporating deep learning and hybrid models with finite element analysis for even more robust predictions.

RESULTS AND DISSCUSSION

We carried reference material from several journals to apply the machine learning algorithms for the prediction of strength of the CFST columns confined by CFRP. This method consumes much less time in estimating strength as it eliminates the necessity of labor or any machinery. Column strength can be predicted effectively and accurately using such algorithms, and every one of them has varied strengths and capabilities in prediction.

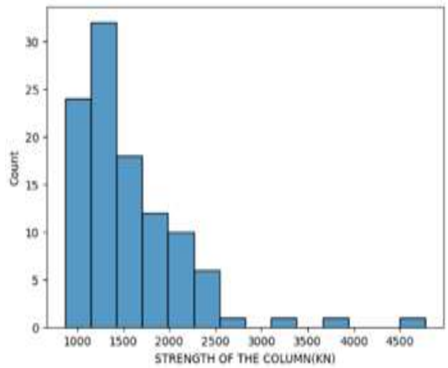
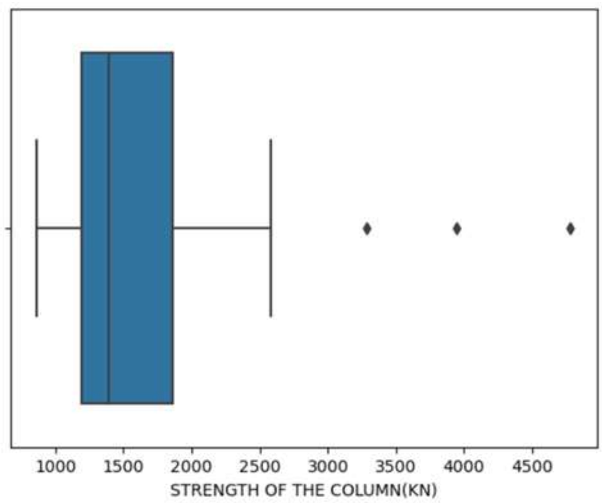


Figure 1 : Histogram

The histogram shows that strength values for columns of CFRP confined CFST are nearly normally distributed within kN. Most columns fall in the ranges of strengths from 1000 kN to 2000 kN, and most frequencies lie in the ranges of 1000-1500 kN; hence this is their general strength in the data used. This histogram is right skewed because it only has a few columns having very high marked strengths that range from 4000-4500 kN. This plot does bring out the common strength range for these columns, although, it does illustrate the few very high strength columns.



2 : Box plot

Above is a box plot showing the spread of strength values for CFST columns confined with CFRP in kN. The middle part is the interquartile range, that includes middle 50% values mostly between about 1250 and 2000 kN, and median strength at about 1500 kN. Whiskers are taken as extended to lowest and highest values in a normal range. Outliers are plotted as points outside the whiskers. This means that there are few columns whose strength values are much higher than 3000 kN. This provides a plot of a normal distribution, which might reveal typical strength ranges but could indicate the presence of outliers of high strength.

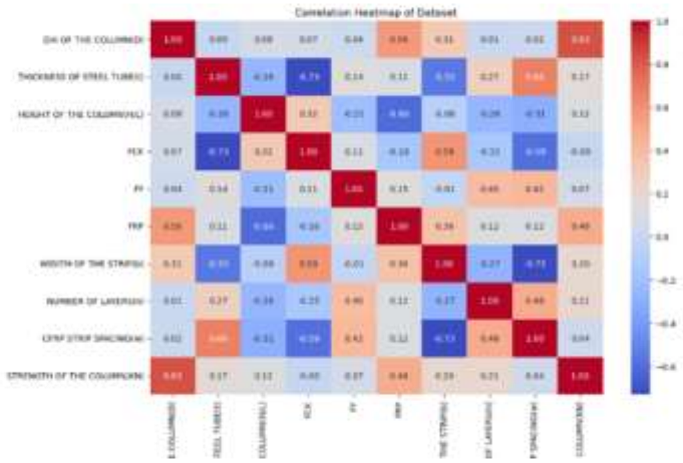


Figure 3: Heatmap

This is a heatmap of the extent to which the various structural parameters are related to each other in a dataset. Red was used to highlight areas in positive association highly as variables increase with each other, and, in blue areas, a connection can be said to hold even when one increases inversely to the other in regard to increase and a respective decrease. Some key findings are: The column diameter versus column strength has very positive correlation; the bigger the columns are in diameter, the stronger they are usually. Concrete compressive strength, FCK, versus the thickness of the steel tube is a very negative correlation: the stronger the concrete is, the smaller is the thickness of the steel tube. This could be an indicator for using thinner steel tubes but with higher concrete strength. The visualization helps in quick identification of strongly related variables and aids in the interpretation of structural design factors.

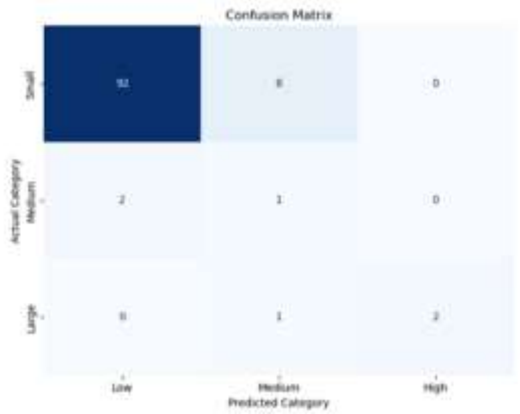


Figure 4 Confusion matrix

This confusion matrix tests the model on three categories: Small, Medium, and Large (actual) against Low, Medium, and High (predicted). The numbers in each cell represent how many times the model predicted a particular category versus the actual category. For instance, it got 92 of "Low" correct for "Small," but made some errors by predicting "Small" as "Medium" 8 times. The matrix lets you see accurate predictions, or correct along the diagonal, and classifications that are wrong off the diagonal, which then becomes very valuable to both the potential accuracy of a model but also to where one might perhaps need to adjust it a little.

Model	Performance
Linear Regression	86.20%
SVM Regression	45.98%
KNN Regression	50.27%
Decision Tree Regression	83.12%
Bagging(Decision Tree)	83.12%
Boosting(Random Forest)	79.43%
Adaptive Boosting	73.31%
Gradient Boosting	86.02%

Figure 5 : Comparison table of the algorithms based on their performance

Based on the performance table, Linear Regression and Gradient Boosting are the best-suited algorithms for this dataset, as they both achieve the highest accuracy, with Linear Regression at 86.20% and Gradient Boosting at 86.02%. These models have demonstrated the strongest predictive capability for estimating the strength of CFRP-confined CFST columns, making them ideal choices for this dataset. If a simpler, more interpretable model is preferred, Linear Regression may be ideal, while Gradient Boosting is likely more robust for capturing complex patterns.

CONCLUSION

- The two top models are Linear Regression and Gradient Boosting, with almost the same accuracy: 86.20% and 86.02%, respectively. These two models are the leaders.
- The worst-performing two models are SVM Regression and KNN Regression, although showing low performance in terms of precision compared to other models such as 45.98% and 50.27%, respectively. This concludes that the models are not suitable for the given task or dataset.
- The tree-based method uses Decision Tree, Bagging with Decision Tree, and Random Forest Boosting. Performance ranges from 79.43% to 83.12%. Therefore, ensemble methods are very good, that is bagging and boosting with tree-based models.

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