https://doi.org/10.48047/AFJBS.6.Si4.2024.122-128

AFJBS

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

PREDICTION OF SHEAR STRENGTH OF FRP RC COLUMNS BY USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

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Volume 6, Issue Si4, 2024

Received: 12 Apr 2024

Accepted: 02 May 2024

doi:10.48047/AFJBS.6.Si4.2024.122-128

Abstract: For designing and evaluating reinforced concrete structures, it is essential to predict the punching shear strength (PSS) of fiber-reinforced polymer reinforced concrete (FRP-RC) beams. This study utilized three meta-heuristic improvement calculations — insect lion enhancer (ALO), moth fire analyzer (MFO), and salp swarm calculation (SSA) — to upgrade hyperparameters of an irregular timberland (RF) model for PSS expectation. The types of column section (TCS), cross-sectional area of the column (CAC), slab's effective depth (SED), span–depth ratio (SDR), compressive strength of concrete (CSC), yield strength of reinforcement (YSR), and reinforcement ratio (RR) were the seven characteristics of FRP-RC beams that were used as inputs. The ALO-RF model with a populace size of 100 exhibited unrivaled expectation execution: MAE of 25.0525, MAPE of 6.5696, R2 of 0.9820 in preparing, and MAE of 52.5601, MAPE of 15.5083, R2 of 0.941 in testing. SED's significant influence on PSS prediction suggests that it plays a crucial role in adjusting PSS. Additionally, the cross-breed AI model streamlined by metaheuristic calculations outperformed customary models in exactness and blunder control, featuring its true capacity for upgrading built up substantial construction plan and appraisal.

Keywords: reinforced concrete; punching shear strength; random forest; ant lion optimizer; moth flame optimizer; salp swarm algorithm

1 . Introduction

Due to their low weight, resistance to corrosion, and high strength, fiber-reinforced polymers (FRPs) are increasingly being used in civil engineering instead of traditional steel reinforcement. Composite structures made of FRP and concrete improve structural resistance and stiffness while reducing the susceptibility of concrete to corrosion, making them suitable for projects like retrofitting, rehabilitating, and fixing things. However, it is still challenging but essential for structural design to accurately assess the shear strength of FRP-reinforced concrete (RC) beams. The shear strength of FRP-RC beams is determined using a variety of approaches, including experimental analysis, numerical simulations, and artificial intelligence (AI) prediction techniques. Though resource-intensive, experimental methods provide intuitive evaluations. Mathematical recreations offer successful investigations however require presumptions about stacking conditions and significant trial information for displaying. When compared to conventional empirical formulas, AI methods like machine learning (ML) models have emerged as effective tools in civil engineering [1-3]. For instance, Mansour et al. used artificial neural networks (ANNs) to predict the performance of RC beam shear, showing that ANNs were more accurate than empirical approaches. Abuodeh et al. investigated the various factors that influence FRP's effect on RC beam shear stress with resilient back-propagating neural networks (RBPNNs). Support vector regression (SVR), which was optimized by the African vulture's optimization algorithm (AVOA), was used by Kaloop et al. to predict RC deep beam shear strength with minimal error. Regardless of progressions, challenges continue. Due to the complex, nonlinear nature of predicting FRP-RC beam shear strength, SVR models require precise kernel function and hyperparameter selection, whereas ANNs require meticulous structuring. Future exploration should address these intricacies to additional improve forecast precision and pertinence in primary designing [4-5].

The Irregular Backwoods (RF) model, a strong gathering AI (ML) procedure contrived by Breiman, consolidates various choice trees to upgrade vigor and moderate overfitting. Predicting mechanical properties has been a success in construction engineering, particularly in applications involving reinforced concrete (RC). For predicting various aspects of RC strength and performance, studies by Mohammed et al., Zhang et al., and Feng et al. have consistently demonstrated that RF is superior to other machine learning models like support vector machines (SVM) and back-propagation neural networks (BPNN). With regards to foreseeing the punching shear strength (PSS) of fiber-built up polymer supported concrete (FRP-RC) radiates, this paper utilizes RF models advanced by three metaheuristic calculations: subterranean insect lion enhancer (ALO), moth-fire streamlining (MFO), and salp swarm calculation (SSA). As shown by their successful application in civil engineering tasks like soil shear strength prediction and damage assessment in concrete beams, these metaheuristic algorithms are adept at optimizing hyperparameters to improve ML model performance. The construction of this paper is illustrated as follows: Area 2 presents the ALO, MFO, and SSA calculations related to the RF model. The PSS database's preparation for FRP-RC beams, the steps involved in data preprocessing, and the metrics used to evaluate model performance are all described in detail in Section 3. Area 4 presents the prescient results of the half and half models and thinks about their adequacy, including highlight significance investigation for deciphering expectation execution. At long last, Area 5 sums up the review's discoveries and proposes roads for future examination in enhancing RF models for anticipating FRP-RC shaft PSS, featuring the capability of metaheuristic calculations in progressing underlying designing applications [6-7].

2. Methodologies

2.1. Random Forest

Leo Breiman came up with the random forest algorithm in 2001, which is a popular ensemble learning method that improves accuracy and robustness by creating multiple decision trees during training that then vote for the final prediction together. It utilizes "stowing," where different choice trees are developed by arbitrarily examining the preparation information with substitution. Further enhancing the trees' randomness and diversity is the random selection of a subset of features to split at each node of the decision tree. Each tree makes a decision during prediction, and the majority vote determines the final prediction, lowering the likelihood of overfitting and improving the model's generalizability [8].

2.2. The Ant Lion Optimizer

The insect lion streamlining agent (ALO), proposed by Mirjalili, is propelled by the hunting conduct of insect lions and succeeds in tackling complex advancement issues productively. The calculation makes an inquiry space displayed after a subterranean insect lion's pit. In ALO, the subterranean insect's development investigates the pursuit space, while the lion's conduct takes advantage of it. By restricting the ants' erratic movement to a hypersphere layer surrounding a trap, a roulette strategy mimics the hunting process. The ant lion sprays sand to bring an ant closer if it falls into the trap. Every emphasis holds the best arrangement, impacting future emphasess and guaranteeing ideal outcomes through a tip top system [9].

2.3. The Moth–Flame Optimization

Seyedali Mirjalili's 2015 invention of the moth–flame optimization (MFO) algorithm is based on the way moths navigate at night by keeping a fixed angle with the moon for straight flight. Moths are guided toward the global optimum by the MFO algorithm, which employs a distance-based sorting mechanism and logarithmic spirals. In this calculation, every moth refreshes its position comparative with a remarkable fire, assisting with staying away from nearby optima. Moths consistently move inside the pursuit space, focusing on the place of their relating fire [10].

2.4. The Salp Swarm Algorithm

In 2014, Mirjalili et al. proposed the salp swarm algorithm (SSA), a bio-inspired optimization technique. SSA is roused by the swimming way of behaving of salps, which are barrel-formed planktonic tunicates that move by contracting and extending their bodies. During the scavenging and development in the sea, salps frequently follow each other in a chain-like way, with people associated head-to-tail. In such a "chain" bunch, there are pioneers and supporters, with the pioneers liable for following food and every devotee just impacted by the salp before it.

3. Data Manipulation and Performance Evaluation

3.1. Punching Shear Strength of FRP-RC Beams

A crucial mechanical property of fiber-reinforced polymer-reinforced concrete (FRP-RC) beams is their punching shear strength (PSS), which indicates their capacity to resist shear force at concentrated load points like columns. PSS is affected by variables, for example, segment area types, segment cross-sectional region, piece viable profundity, length profundity proportion, concrete compressive strength, support yield strength, and support proportion. To get the most out of the performance and design of FRP-RC structures, it's important to know these things. AI (ML) models have arisen as compelling instruments for anticipating PSS, offering more exact and proficient expectations than customary techniques by gaining designs from broad exploratory information [11].

3.2. Construct Database

This study expected to make an extensive data set of punching shear strength (PSS) for FRP-RC sections by gathering information from 26 distributed works. The data set contains data on a few boundaries, which can be ordered as follows: (1) mathematical boundaries, including the kind of segment area (TCS) addressed by 1, 2, and 3 for roundabout, rectangular, and square sections, individually, cross-sectional region of the segment (CAC), piece's powerful profundity (SED), and range profundity proportion (SDR); (2) substantial strength data, including the compressive strength of cement (CSC); and (3) steel support data, including the yield strength of support (YSR) and support proportion (RR) [12].

3.3. Parameter Correlation Analysis

Before creating a machine learning (ML) model, performing a correlation analysis on the parameters helps determine the strength and direction of relationships between input variables. The Pearson connection coefficient is a factual measure that assesses the direct connection between two persistent factors, going from −1 to +1. A value of 1 indicates a linear relationship that is completely negative, 0 indicates no linear relationship, and +1 indicates a linear relationship that is completely positive. This examination is usually utilized in ML models to evaluate the relationship between's feedback boundaries. In order to avoid data redundancy, it may be necessary to select or eliminate particular parameters if the correlation coefficient between the input parameters is high (typically greater than 0.8) [13].

3.4. Evaluation Indicators

The selection of appropriate evaluation metrics is a crucial factor in determining the models' accuracy and reliability when building various machine learning (ML) models. Evaluation metrics for regression models include the coefficient of determination (R2), the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the mean absolute error (MAE) for solving regression problems. The MAE estimates the typical outright contrast between the anticipated qualities and the deliberate qualities, which gives a proportion of the precision of the model in foreseeing the objective variable; the MAPE estimates the typical rate distinction between the anticipated qualities and the deliberate qualities; and the R2 is a factual measure that addresses the extent of the difference in the objective variable that can be made sense of by the free factors in the model. It goes from 0 to 1, with higher qualities showing a superior fit between the model and the information; the RMSE estimates the root mean squared contrast between the anticipated qualities and the deliberate qualities. In this review, MAE, MAPE, R2, and RMSE are chosen as assessment measurements for the ML model [14].

4. Results and Discussion

4.1. Model Validity Judgment

Because it takes into account both the magnitude and direction of errors, the root mean square error (RMSE) is a widely used evaluation metric in machine learning. This makes RMSE reasonable as the wellness or goal capability in improvement calculations, which mean to find the ideal arrangement of model boundaries that limit expectation blunders. Hyperparameters in the RF model was optimized using three optimization algorithms—ALO, MFO, and SSA—in this study to predict the punching shear strength (PSS) based on FRP-RC beam characteristics. RMSE was utilized as the wellness worth to look for the best hyperparameter mix, with the objective of ceaselessly limiting this wellness esteem. Although convergence results were comparable for population sizes of 50, 100, and 200, the ALO-RF model converged the fastest with a population size of 200. A population size of 100 produced superior convergence results for the MFO-RF models. The SSA-RF models with populace sizes of 100 or 200 accomplished lower last union wellness values contrasted with different models. ALO-RF and MFO-RF demonstrated faster convergence speeds than SSA-RF among the three hybrid models, indicating that ALO and MFO have more sensitive search capabilities for optimizing RF hyperparameters for predicting PSS. However, the fact that none of the three hybrid models' final convergence fitness values were significantly different suggests that additional research is required to determine how well they can predict PSS in FRP-RC beams [15].

4.2. Hybrid Models Performance Evaluation

This study determined four evaluation metrics—MAE, MAPE, R2, and RMSE—for each model in order to provide a comprehensive evaluation of the predictive capabilities of ALO-RF, MFO-RF, and SSA-RF for PSS. The models were ranked according to how well they did in each metric, with the best model getting four points and the worst one. The best model was chosen because it had the highest overall score. ALO-RF (population = 100), MFO-RF (population = 10), and SSA-RF (population = 50) were also compared to an unoptimized RF model that was trained and tested on the same dataset in the study. Plots were used to illustrate the comparison, with points closer to the diagonal dashed line indicating superior prediction performance. The distribution of differences between predicted and measured values was depicted in the difference distribution plot in the upper right corner. The blunder circulation uncovered that ALO-RF (Pop = 100) had mistaken fundamentally inside the scope of [-20, 20], MFO-RF (Pop = 10) inside [-40, 40], and SSA-RF (Pop = 50) inside [-60, 60], showing that ALO-RF (Pop = 100) had a more modest mistake range in foreseeing the PSS for FRP-RC radiates [16].

Table 1. Parameter setting of RF model.

Model	**Hyperparameter**	**Typical Default Values**
RF	mtry samples size node size	*v*/3 for regression n 5 (for regression)
	number of trees	1000
	splitting rule	Gini impurity

Note: n is the number of observations and v is the number of variables in the dataset.

In view of the extensive examination, ALO-RF (Pop = 100) exhibited the best prescient execution, with MAE of 25.0525, MAPE of 6.5696, R2 of 0.9820, and RMSE of 59.9677 in the preparation set, and MAE of 52.5601, MAPE of 15.5083, R2 of 0.941, and RMSE of 101.6494 in the testing set. The RF model's ability to capture the intrinsic relationship between the input parameters and PSS of FRP-RC beams is enhanced by these findings, which demonstrate that the ALO algorithm with a population size of 100 is capable of effectively capturing the optimal combination of hyperparameters. For evaluating the PSS of FRP-RC beams, Feng et al. developed various ML algorithms, but these models were restricted to conventional, independent ML methods. Interestingly, the current exploration utilizes a RF model with upgraded capacity to forestall overfitting and utilizes three metaheuristic enhancement calculations to tune the RF model's hyperparameters, further developing forecast exactness. To approve the proposed prescient model's adequacy, the best presentation of the ALO-RF model was contrasted and different models created utilizing a similar information base. The ALO-RF model provides a better explanation of the connection between the input parameters and the PSS of FRP-RC beams, as evidenced by higher R2 values, according to the findings. Predictions that are more accurate and reliable can be made by adapting and fine-tuning this method to address specific difficulties or research questions in various fields [17-18].

4.3. Importance Evaluation of Feature Parameters

An essential step in comprehending the underlying relationships between the target variable and the input features is the feature importance analysis, which can be utilized to enhance the model's performance and interpretability. RF can give significant experiences into the overall significance of various elements in foreseeing the objective variable. Researchers are able to identify the most important features for the task at hand thanks to this method's quantitative assessment of each feature's contribution to the model's predictive performance. The significance scores of each information variable in the RF model, and as per the information in the figure, it very well may be seen that chunk's powerful profundity (SED) has the most elevated significance score among all the component boundaries of FRP-RC radiates. The outcome features the cozy connection among SED and PSS, which assumes an unmistakable part in foreseeing the PSS in light of the ALO-RF model. Albeit the significance scores of CAC, CSC, RR, SDR, YSR, and TCS are lower contrasted with SED, they actually have a critical hidden relationship with PSS. Overall, of all the parameters, slab's effective depth (SED) makes the most contribution to predicting PSS. This suggests that SED and PSS have a strong internal relationship, and changing SED can effectively control PSS variation [19-20].

5. Conclusions

This study investigates the viability of three metaheuristic enhancement calculations (ALO, MFO, and SSA) in streamlining arbitrary timberland (RF) model hyperparameters for anticipating the punching shear strength (PSS) of FRP-RC radiates. Results show that the ALO-RF model accomplishes quicker assembly rates contrasted with MFO-RF and SSA-RF, recommending uplifted responsiveness of ALO and MFO in upgrading hyperparameters for PSS expectation utilizing RF. Particularly, the ALO-RF model with a population size of 100 demonstrates the highest predictive accuracy thanks to its higher correlation coefficient and narrower error distribution range. Slab's effective depth (SED) is found to be the input parameter with the greatest influence on PSS prediction, highlighting its role in controlling PSS variations. Be that as it may, the shortage of trial information represents a huge test to precisely foreseeing FRP-RC bar execution, impeding model turn of events and approval. Prediction efforts are further complicated by the intricate interaction between the concrete matrix and the FRP reinforcement. While cutting edge AI and improvement calculations offer precise forecasts, they frequently require significant computational assets, prompting broadened preparing and expectation times. Future examination ought to zero in on growing exploratory datasets for FRP-RC pillars to upgrade prescient model quality and pertinence. Additionally, developing prediction models that are more accurate and trustworthy will be made easier by expanding our comprehension of the FRP reinforcement-concrete matrix interactions.

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