



Journal of Materials and Engineering Structures

Research Paper

Predicting shear capacity of Recycled Aggregate Concrete beams using Artificial Neural Network

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ARTICLE INFO

Article history:

Received : 14 November 2024

Revised : 24 December 2024

Accepted : 24 December 2024

Keywords:

RAC

ANN

MLP

Eurocode 2

ACI318-14

ABSTRACT

This study investigates the application of an Artificial Neural Network (ANNs) utilizing a Multi-Layer Perceptron (MLP) architecture to predict the shear capacity of Recycled Aggregate Concrete (RAC) beams. The ANNs model was trained using the Levenberg-Marquardt algorithm with a comprehensive dataset comprising 232 experimental shear tests, reflecting a wide range of variables relevant to RAC beam performance. The model's predictions were compared to those derived from established design standards, including ACI 318-14 and Eurocode 2, to evaluate its performance. Various statistical criteria were employed to assess the model's accuracy and reliability in predicting shear strength, including metrics that measure goodness of fit, error rates, and predictive consistency. This research highlights the growing potential of machine learning techniques in civil engineering, particularly for enhancing the precision of shear strength predictions for RAC beams. The findings suggest that the ANN model offers a valuable alternative to traditional prediction methods, with the potential to improve accuracy and address some of the limitations inherent in conventional design standards.

1 Introduction

In recent years, sustainability and green practices in civil engineering have become essential developments worldwide. The building and transport industries produce a large volume of “Construction Demolition Waste” (CDW), which includes a variety of materials such as plastic, wood, glass, metal and concrete. Recycling CDW is a valuable method for lowering its environmental impact and conserving natural resources. One approach that has gained attention globally is the use of recycled aggregate concrete (RAC), where natural aggregates are partially or fully replaced with recycled materials from construction waste. Studies have shown that recycled aggregate concrete (RAC) generally has higher water absorption, lower compressive strength, similar freeze-thaw resistance, and greater dry shrinkage compared to normal aggregate concrete (NAC) [1].

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When designing concrete and reinforced concrete (RC) beams (Fig. 1), shear capacity is a crucial consideration, as shear failure is directly associated with the failure mode of girders subjected to flexural loading. To promote sustainability in civil engineering, researchers have extensively conducted both experimental and theoretical studies to explore innovative design concepts and enhance shear strength. For instance, Arezoumandi et al. [2] investigated the effects of using 100% recycled coarse aggregate (RCA) on the shear strength of RC beams, taking reinforcement ratios into consideration. Their findings indicated a reduction in shear strength of approximately 10-15% when RCA was used. Similarly, Younis et al. [3] examined the shear strength of RC beams incorporating recycled aggregate concrete (RAC) and glass fiber-reinforced polymer (GFRP) stirrups. Results showed that, on average, the shear strength of RC beams with RAC decreased by 12%, and the GFRP stirrups demonstrated lower ductility compared to steel stirrups. Research on shear strength design using various approaches has been widely conducted and continues to expand [4-7]. In general, research indicates that RAC beams generally exhibit lower shear capacity than NAC beams, even when they have identical reinforcing and shear-span ratios [3, 8]. The shear strength of RAC beams is influenced by various factors, such as geometric dimensions, the properties of RAC, the recycled aggregate replacement ratio, the longitudinal reinforcement ratio, the shear-span ratio, and the stirrup ratio [9]. Furthermore, shear design methodologies in standards like ACI 318-14 [10] and Eurocode 2 [11] involve certain assumptions and simplifications, which can reduce accuracy and increase the variability of computed results.

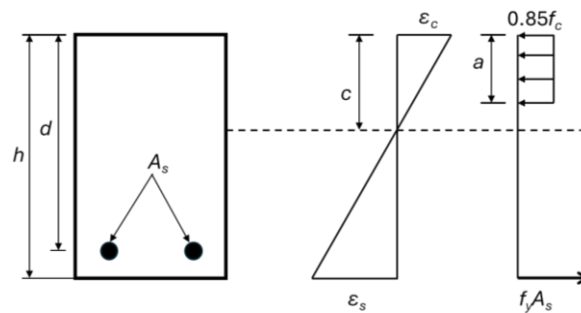


Fig. 1 – Typical cross section of a reinforced beam

With the rapid rise of data-driven methods in civil engineering, machine learning (ML) has emerged as an efficient approach for predicting the performance of structural members. For instance, Rahman et al. [12] used a machine learning approach to predict the shear strength of steel fiber-reinforced concrete (SFRC) beams, utilizing data from 507 experimental results. The results revealed that traditional equations frequently underestimate the shear strength of SFRC beams, whereas the XGBoost model delivered the most accurate predictions. Yaseen [13] examined three different machine learning models to predict the shear strength of FRP-reinforced concrete beams with transverse reinforcement. In addition, Solhmirzaei et al. [14] used support vector machine regression and multigene genetic programming to predict the flexural capacity of Ultra-High Performance Concrete beams.

Recognizing the effectiveness of machine learning (ML) in predicting beam shear strength, this study seeks to develop an artificial neural network (ANNs) model with a multi-layer perceptron (MLP) architecture to forecast the shear capacity of recycled aggregate concrete (RAC) beams. The ANN model was trained using the Levenberg-Marquardt algorithm. A database comprising 232 experimental shear tests was compiled from the literature, and the model's results were validated against analytical predictions from ACI 318-14 and Eurocode 2.

2 Proposed model and data collection

2.1 Artificial Neural Network – ANN

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functioning of biological neural networks. They are particularly effective for addressing complex problems that traditional mathematical models often struggle to solve. An ANN typically consists of three main components: the input layer, hidden layers, and the output layer (as shown in Figure 2). During training, the network learns from input data, adjusts its internal parameters, and applies these learned patterns to make predictions on new, unseen data.

In this study, a Multi-Layer Perceptron (MLP) was developed using MATLAB version R2023b. The MLP architecture consisted of an input layer, one or more hidden layers, and an output layer. This multi-layer network allows for the identification of nonlinear relationships and supports accurate predictions. A trial-and-error method was employed to select the optimal number of neurons in the hidden layer, ranging from 10 to 30. This method ensures that the model is neither too simple (underfitting) nor too complex (overfitting). The Levenberg-Marquardt algorithm was utilized for training and a learning rate of 0.01 was set to balance convergence speed and accuracy. This algorithm is recognized for its efficiency in training, as it combines the benefits of gradient descent and the Gauss-Newton method, resulting in faster convergence and enhanced performance, particularly when dealing with many input parameters, such as in the shear design of RAC beams. To identify the optimal neural network model, the datasets were divided into training (70%), testing (15%), and validation (15%) sets. It can be explained that this split ensures that the model is trained on the majority of the data, with validation preventing overfitting and testing providing an unbiased evaluation of the model's performance.

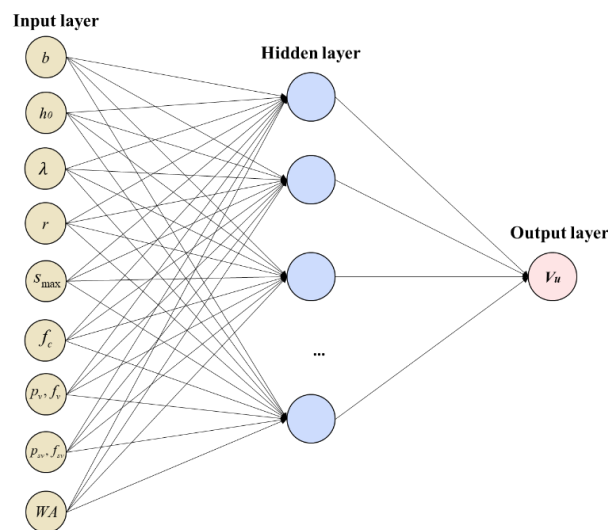


Fig. 2 – Architecture of the ANN model

Table 1 – Geometric and properties of the RAC beams

No.	Parameter	Details	Unit
1	b	beam width	mm
2	h_0	effective depth	mm
3	λ	shear-span ratio	-
4	r	replacement ratio of recycled coarse aggregate (RCA)	100%
5	s	maximum aggregate size	mm
6	f_c	compressive strength of RAC	MPa
7	ρ_y	product of reinforcement ratio	%
8	f_y	yield strength of steel bars	MPa
9	ρ_{sv}	product of stirrup ratio	%
10	f_{yv}	yield strength of stirrups	MPa
11	WA	weighted water absorption of mixed coarse aggregate	%
12	V_u	Shear strength	kN

2.2 Data collection

To build the ANN-MLP model for predicting the shear capacity of RAC beams, the dataset used includes 232 specimens tested from literature, as listed in the appendix of [15]. The input parameters encompass detailed information on the RAC mix proportions, the characteristics of coarse aggregates, and the strength properties of both steel bars and concrete.

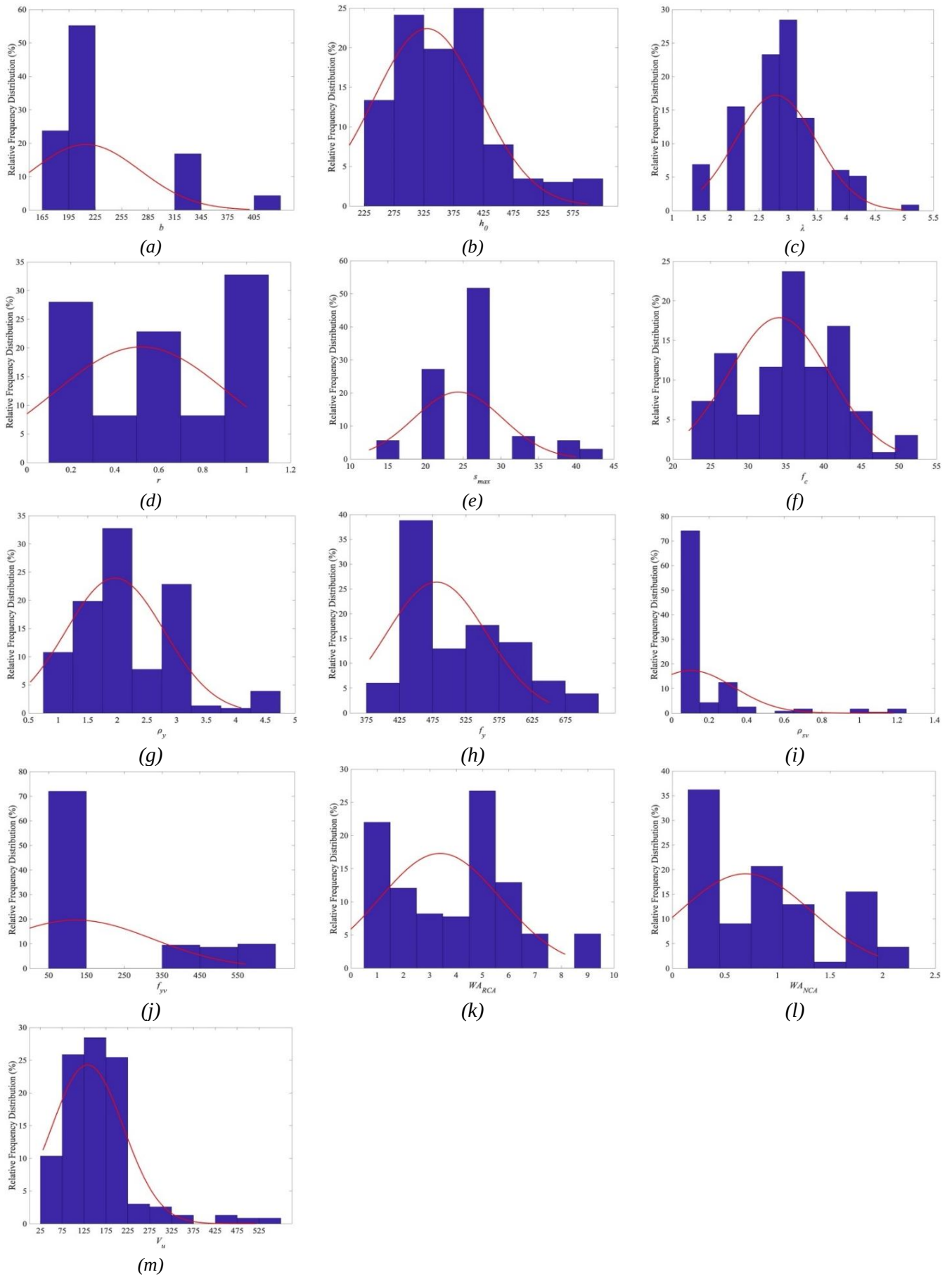


Fig. 3. Distribution of variations

Specifically, the inputs include three geometric parameters: beam width, effective depth, and shear-span ratio, as well as six material parameters: the replacement ratio of recycled coarse aggregate (RCA), maximum coarse aggregate size, compressive strength of RAC, nominal strength of longitudinal reinforcement (calculated as the product of reinforcement ratio and yield strength of steel bars), nominal strength of stirrups (determined by the product of stirrup ratio and yield strength of stirrups), and the weighted water absorption of the mixed coarse aggregate. The output parameter is the shear strength V_u . Table 1 presents the geometry and properties of the RAC beams, while Figure 3 illustrates the distribution of these variables.

3 Comparison of ML model and existing standards

3.1 Existing standards

To verify the predictions from the ANN-based model, the shear strength V_u of RAC beams was also predicted using the ACI 318-14 and Eurocode 2 standards. The expression for V_u can be represented within a unified framework

$$V_u = V_c + bh_0 \rho_{sv} f_{yv} \delta = \sum_{i=1}^s e^H(\omega_i) e(\omega_i) \quad (1)$$

in which V_c is the shear strength capacity of concrete.

According to the ACI 318-14, V_c can be determined as follows

$$V_c = \begin{cases} bh_0 \left(0.167 \sqrt{f_c} + 17 \frac{\rho_y}{\lambda} \right), & (\lambda \geq 2.5) \\ bh_0 \left(3.5 - \frac{2.5}{\lambda} \right) \left(0.167 \sqrt{f_c} + 17 \frac{\rho_y}{\lambda} \right), & (\lambda < 2.5) \end{cases} \quad (2)$$

In Eurocode 2, V_c can be calculated using following formula

$$V_c = 0.12bh_0(1 + \sqrt{(200/h_0)}) [\rho_y (f_c - 8)]^{1/3} \quad (3)$$

3.2 Performance criteria

In this study, three statistical criteria are employed to assess the performance of the ANN model and validate with the experimental data: the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The coefficient of determination (R^2) measures the proportion of variance in the actual values that is predictable from the model, with higher values indicating better model performance. RMSE quantifies the average deviation between actual and predicted values, reflecting the model's accuracy. MAPE represents the relative error of predictions as a percentage of the actual values, providing insight into the model's accuracy in percentage terms. Lower RMSE and MAPE values indicate greater model accuracy. The formulas for calculating R , RMSE and MAPE are as follows

$$R^2 = \left[\frac{\sum_{i=1}^k (m_i - \bar{m}_i)(n_i - \bar{n}_i)}{\sqrt{\sum_{i=1}^k (m_i - \bar{m}_i)^2 \sum_{i=1}^k (n_i - \bar{n}_i)^2}} \right] \quad (4)$$

$$RMSE = \sqrt{\frac{1}{k} \sum_{i=1}^k (m_i - n_i)^2} \quad (5)$$

$$MAPE = \frac{1}{k} \sum_{i=1}^k \left| \frac{m_i - n_i}{m_i} \right| \quad (6)$$

3.3 Results and Discussions

Figure 4 displays the shear strength V_u of RAC beams predicted by the Eurocode 2, ACI 318-14, and the ANN model compared to experimental data. As shown in Figure 4c, the ANN model predictions align closely with the empirical data. Additionally, statistical analysis was performed to evaluate the model's performance, with results presented in Figure 4c. The ANN model achieved an R^2 value of 0.9675, indicating that 96.75% of the variation in the actual values is accurately captured by the model, demonstrating a strong correlation between predicted and actual data. The RMSE of 22.78 signifies that, on average, the model's predictions deviate from the actual values by approximately 22.78 units, reflecting a good level of accuracy. Additionally, the MAPE of 9.06% shows that the average error in predictions is 9.06% of the actual values, providing further evidence of the model's predictive reliability.

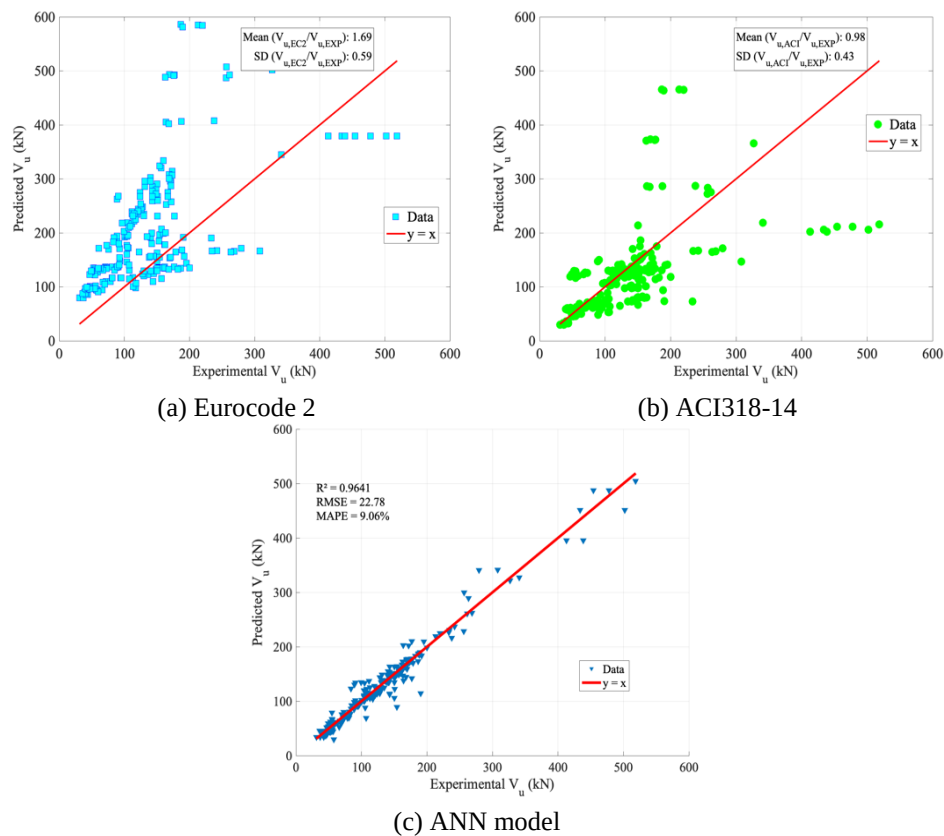


Fig. 4. Comparison of predicted and experimental parameters for ANN models and existing codes

Regarding Eurocode 2, Figure 4(a) shows that, in general, the predicted shear strength from Eurocode 2 equations is higher than the experimental results, with a mean ratio of 1.69. In contrast, the predictions from ACI 318-14 are closer to 1, suggesting that these predictions are more reliable. However, both Eurocode 2 and ACI 318-14 exhibit relatively high standard deviations, indicating that their predictions are less stable for the shear strength of RAC beams. It can be explained that both codes primarily consider the geometric aspects of RAC beams but do not account for nominal parameters such as replacement ratios, maximum size of coarse aggregates, or water absorption of mixed aggregates.

4 Conclusion

In this study, an Artificial Neural Network (ANN) with a Multi-Layer Perceptron (MLP) architecture was developed to predict the shear capacity of Recycled Aggregate Concrete (RAC) beams using a dataset of 232 experimental tests. The ANN model demonstrated strong performance, with a coefficient of determination (R^2) of 0.9675, a Root Mean Square Error

(RMSE) of 22.78, and a Mean Absolute Percentage Error (MAPE) of 9.06%. When compared to traditional design codes such as ACI 318-14 and Eurocode 2, the ANN model outperformed these standards in aligning with experimental data. The predictions from ACI 318-14 and Eurocode 2 exhibited substantial deviations from the experimental results, primarily because these codes do not fully account for nominal parameters specific to RAC beams, such as replacement ratios and water absorption of aggregates. To enhance the accuracy and reliability of shear capacity predictions, it is recommended that future revisions of ACI 318 and Eurocode 2 incorporate equations that consider these nominal parameters of RAC beams. Such adjustments would address the current limitations of these standards and improve the precision of design methodologies for RAC beams.

Acknowledgment

This research is funded by the Ministry of Education and Training (MoET), Vietnam under the grant number B2024-GHA-10.

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