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Machine Learning-Based Prediction of Steel–Recycled Aggregate Concrete Bond Stress: A Comparative Study of Artificial Neural Networks and Empirical Models

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Abstract

This study investigates the bond behavior between steel reinforcement and recycled aggregate concrete (RAC) using two predictive approaches: empirical formulations and artificial neural networks (ANN). A comprehensive dataset of pull-out experimental test compiled from previous research was utilized to develop four empirical equations, each tailored to a specific range of RAC compressive strength. The equations incorporate key parameters including: concrete compressive strength, the ratio of concrete cover to steel bar diameter, the ratio of steel bar diameter to bond length, the replacement ratio of coarse recycled aggregates, the water-to-cement ratio, and the product of steel bar area and yield strength.

The ANN model was structured with an input layer reflecting the same parameters used in the empirical equations, a hidden layer containing 20 neurons, and an output layer representing bond stress. Training was conducted using the collected dataset, while validation was performed against experimental results from 30 experimental pull-out specimens performed in the present study.

While the empirical models yielded reasonable predictions, the ANN demonstrated superior accuracy and robustness in replicating experimental bond stress values. These findings affirm the potential of ANN as a reliable tool for predicting steel-RAC bond behavior.

Keywords: artificial neural network (ANN); bond stress; recycled aggregate concrete (RAC); replacement ratio.

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Introduction

Post-disaster reconstruction, particularly following earthquakes, generates substantial volumes of demolition waste, underscoring the urgent need for sustainable recycling strategies (Xiao et al., 2023). One promising solution is the use of recycled aggregate concrete (RAC), which offers both environmental and economic benefits. By replacing natural aggregates with recycled ones, RAC not only addresses the issue of waste disposal but also helps bridge the gap between material demand and supply in crisis recovery scenarios (Han et al., 2023). Despite its advantages, RAC presents notable challenges in terms of mechanical and durability performance, which limits its widespread structural application (Zaharieva & Dimitrov, 2023; Diab & Danhash, 2023; Diab & Danhash, 2024; Danhash et al., 2023; Mohamad et al., 2025; Wardeh et al., 2017).

One of the most critical aspects of RAC performance is the bond behavior between steel reinforcement and concrete. This bond governs the transfer of axial forces and plays a vital role in structural resilience during seismic events, where premature bond failure can lead to catastrophic consequences. Conventional design standards, developed for natural aggregate concrete, often fall short when applied to RAC, as numerous studies have demonstrated significant deviations in bond-slip behavior (Danhash et al., 2023; Wardeh et al., 2017; Zhang et al., 2023).

To ensure safe and efficient design, a thorough understanding of steel-RAC bond behavior is essential particularly, in defining the development length and preventing early bond failure. While some researchers have observed a decline in bond strength with increasing replacement ratios (Zhang et al., 2023), others report no consistent trend (Danhash et al., 2024), and some even suggest improved performance with treated recycled aggregates (Prince & Singh, 2014). Empirical models have been proposed to predict steel-RAC bond behavior (Xiao & Falkner, 2007), yet these models often lack the flexibility to accommodate the variability inherent in recycled materials.

Recent advancements in artificial intelligence (AI), particularly Artificial Neural Networks (ANN), offer a powerful alternative for modeling complex material behavior. ANN techniques have shown promise in predicting the mechanical performance of RAC by learning from large datasets and capturing nonlinear relationships among variables (Khademi et al., 2021).

A key factor in achieving accurate bond stress predictions lies in the precise definition of mechanical parameters. Variables such as concrete compressive strength, concrete cover, steel bar diameter, bond length, water-to-cement ratio, and steel yield strength directly influence the bond mechanism. Inadequate characterization of these parameters can lead to misleading predictions and unsafe designs (Abdulahad & Danhash, 2024; Danhash et al., 2024; Danhash et al., 2014a, 2014b, 2014c; Danhash et al., 2013; Danhash et al., 2012), especially under seismic loads (Abdulahad & Danhash, 2025). Therefore, any predictive model must be grounded in a robust understanding of these mechanical properties to ensure reliability and applicability.

This paper aims to predict the bond behavior between steel reinforcement and recycled aggregate concrete using two distinct approaches: empirical modeling and artificial neural networks. The study involves experimental pull-out tests, the development of empirical equations tailored to different compressive strength ranges, and the implementation of an ANN model trained on extensive data. The ANN model was verified using experimental pull-out test performed in the present study.

Experimental program

In order to validate the steel-recycled aggregate concrete bond behavior in this study, five mixes were constructed in accordance with ACI 211, with varying replacement ratios (0%, 25%, 50%, 75%, 100%), and the plasticizer was fixed at 1% of cement weight. For each mix, three pull-out specimens were cast, and in the center of each specimen was a (14 mm) ribbed bar with a bond length equal to five times the bar diameter. The same procedure was repeated for another group of specimens with a (16 mm) ribbed bar. For every mix, three cylindrical specimens were cast in order to determine the compressive strength of the mixes. The type of Portland cement used was

I-32.5, and the superplasticizer "Daracem SP6" which fulfills ASTM-C-494-Type F requirements, was used. The recycled coarse aggregates were obtained by crushing and sieving waste concrete from debris in the laboratory, where crushing and sieving were performed manually. The debris are obtained from damaged buildings before putting them in the landfill. The natural coarse aggregates (NCA) were crushed stone with a maximum diameter of 25 mm, and natural ordinary sand was used for all mixes. Fig. 1 presents the sieve analysis curves of the recycled and natural aggregates. Table 1 provides concrete mix proportions for the standard NAC mix for 1 m^3 in kg. The yield strength of the steel is Fy = 420 MPa, and the geometric characteristics of the ribs are presented in (Fig. 2 and Table 2).

Fig. 1

The sieve analysis curves of the recycled and natural aggregates.

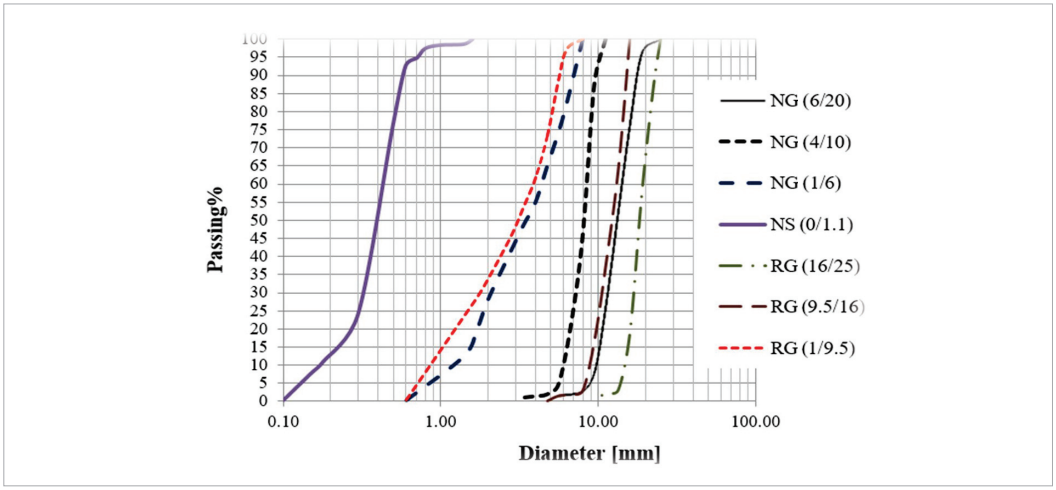


Table 1

Concrete mix proportions

Constituents	Gravel	Sand	Water	Cement	Plasticizer
Dosage (kg/m^3)	1127	672	200	400	1% of cement weight

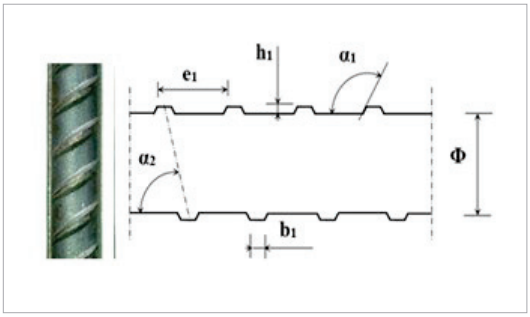
Table 2

The geometrical characteristics of the ribs

Φ(mm)	h_1 (mm)	b_1 (mm)	e_1 (mm)	A_s (mm^2)
14	1.1	1.4	9	153
16	1.2	1.6	9.6	201

Fig. 2

The ribbed steel bar used in the test



The pull-out test was performed on the specimens using the machine INSTRON (5000 kN) to obtain the values of the load, where the loading speed was manually controlled, (see Fig. 3).

The results of the experimental tests are presented in (Table 3), where L_d is the bond length, is the bar diameter, is the concrete cover, is the bond stress of the mix, R is the replacement ratio, W/C is the water to cement ratio, F_y is the yield stress of the bar, and As is the area of the steel bar. The mean bond stress and the compressive strength of each mix are presented in Table 4, where the decrease in bond stress and compressive stress are calculated depending on the reference mix which is the mix with natural aggregate. The results showed that the increase in replacement ratio decreased the compressive strength by 7.7%, 6.6%, 9.3%, and 13.1% for the replacement ratios of 25, 50, 75, and 100%,

as presented in **Table 4**. The experimental results show that incorporating recycled aggregates in concrete led to a decrease in the bond strength between steel and concrete, affecting the steel-concrete bonding adversely. The bond stress decreased for the specimens with (14 mm) of steel bar diameter by about 23.5%, 25.7%, 30.6%, and 34.9% for the replacement ratios 25, 50, 75, and 100%, while it was for the specimens with (16 mm) of steel bar diameter by about 29.5%, 31.6%, 33.1%, and 38.6% for the replacement ratios 25, 50, 75, and 100%, see **Table 4**.

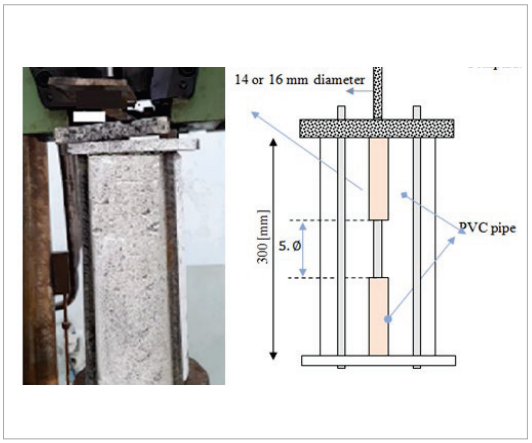


Fig. 3

Pull-out test setup

Table 3

The results of the pull-out test

F'_c [MPa]	L_d [mm]	d_b [mm]	C_c [mm]	$\tau_{exp\ i}$ [MPA]	τ_{exp} [MPA]	R (RCA)	W/C	F_Y [MPA]	A_S [mm²]
22.5	80	16	67	11.66	11.52±0.15	100%	0.5	420	201
	80	16	67	11.52		100%	0.5	420	201
	80	16	67	11.37		100%	0.5	420	201
23.5	80	16	67	12.37	12.56±0.24	75%	0.5	420	201
	80	16	67	12.80		75%	0.5	420	201
	80	16	67	12.51		75%	0.5	420	201
24.2	80	16	67	12.51	12.84±0.74	50%	0.5	420	201
	80	16	67	13.22		50%	0.5	420	201
	80	16	67	12.80		50%	0.5	420	201
23.9	80	16	67	13.08	13.22±0.14	25%	0.5	420	201
	80	16	67	13.36		25%	0.5	420	201
	80	16	67	13.22		25%	0.5	420	201
25.9	80	16	67	18.20	18.77±0.57	0%	0.5	420	201
	80	16	67	18.77		0%	0.5	420	201
	80	16	67	19.34		0%	0.5	420	201
22.5	70	14	68	12.35	12.56±0.76	100%	0.5	420	153.9
	70	14	68	13.32		100%	0.5	420	153.9
	70	14	68	12.02		100%	0.5	420	153.9
23.5	70	14	68	13.97	13.40±0.73	75%	0.5	420	153.9
	70	14	68	12.67		75%	0.5	420	153.9
	70	14	68	13.65		75%	0.5	420	153.9
24.2	70	14	68	14.26	14.35±0.81	50%	0.5	420	153.9
	70	14	68	15.16		50%	0.5	420	153.9
	70	14	68	13.65		50%	0.5	420	153.9
23.9	70	14	68	15.27	14.77±0.50	25%	0.5	420	153.9
	70	14	68	14.62		25%	0.5	420	153.9
	70	14	68	14.43		25%	0.5	420	153.9
25.9	70	14	68	20.32	19.31±0.81	0%	0.5	420	153.9
	70	14	68	19.11		0%	0.5	420	153.9
	70	14	68	18.50		0%	0.5	420	153.9

The ideal replacement ratio of natural aggregates with recycled aggregates is 50%, which gives an acceptable bond stress equal to (14.35 MPa) for (14 mm) bar, and (12.84 MPa) for (16 mm) bar, while the compressive strength is (24.2 MPa) with a decrease of 6.6% in comparison with the reference mix with natural aggregates.

Table 4
The compressive strength and bond for the mixes

Replacement ratio%	R=0	R=0.25	R=0.50	R=0.75	R=1
F'_c [MPa]	25.9±0.46	23.9±0.32	24.2±0.26	23.5±0.18	22.5±0.22
$\frac{F'_{cR=0\%} - F'_{cR\%}}{F'_{cR=0\%}} \times 100\%$	-	7.7%	6.6%	9.3%	13.1%
τ_{exp} [MPa] d = 14 [mm]	19.3	14.77	14.35	13.40	12.56
$\frac{\tau_{R=0\%} - \tau_{R\%}}{\tau_{R=0\%}} \times 100\%$	-	23.5%	25.7%	30.6%	34.9%
τ_bond [MPa] d = 16 [mm]	18.77	13.22	12.84	12.56	11.52
$\frac{\tau_{R=0\%} - \tau_{R\%}}{\tau_{R=0\%}} \times 100\%$	-	29.5%	31.6%	33.1%	38.6%

Some researchers concluded that the optimum replacement ratio for recycled aggregates with natural aggregates that provides the best bond stress for steel with recycled aggregate concrete (RAC) is 50% (Imjai et al., 2026), while Sahmi et al. (2025) obtained that the optimum replacement ratio for recycled aggregates with natural aggregates to achieve the best bond stress for steel with recycled aggregate concrete is up to 70%.

The results of the present study concluded that the bond stress decreased with the increase in diameter of the bar, where an increase of 12.5% (from 14 to 16 mm) in bar diameter, the bond stress decreased by about 2.8% of the reference mix bond stress, see Table 4. Previous research findings suggested that the bond strength of a bar embedded in concrete tends to increase as the bar diameter decreases (Lee et al., 2023). Conversely, in RAC, the bond strength may decrease with an increase in bar diameter, as indicated by the pull-out test results on deformed steel bar in RAC (Zou et al., 2020). These contrasting findings highlight the complexity of the bond behavior in different concrete compositions. Therefore, it is important to consider the specific mix design and material properties when evaluating how the bar diameter affects the steel-RAC bond behavior.

Proposing a new empirical relationship

Empirical relations for predicting steel-recycled aggregate concrete bond stress play a crucial role in encouraging sustainable construction practices, as they bridge the gap between theory and practical applications, allowing engineers to confidently incorporate RAC into their designs (Liu et al., 2023).

International standards proposed empirical relations for bond stress in concrete depending on its compression strength, like CEB-FIB, while the Australian code (Standards Australia, 1994) added the ratio of concrete cover to bar diameter. The American standard ACI 408 R-03 added the ratio of bond length to bar diameter and the steel yielding stress to the previous parameters, while other researchers added the replacement ratio to the compressive strength (Seara-Paz et al., 2014; Kim et al., 2015; Wardeh et al., 2017), and the ratio of concrete cover to the bar diameter (Kim et al., 2015). Abdulazeez et al., found that the yield stress of the reinforcing steel bar, which is a parameter investigated in their study, affecting the bond strength behavior of deformed steel bar embedded in (RAC) (Abdulazeez et al., 2021). Fu et al., concluded that the yield stress of steel affects the steel-RAC bond behavior and stress transfer between the longitudinal steel bar and recycled aggregate concrete (Fu et al., 2017).

An analytical investigation on the bond stress of deformed steel bar embedded in recycled aggregate concrete found that the yield stress of steel can influence the bond behavior in recycled aggregate concrete, as analyzed theoretically and experimentally in their study on deformed steel bars in RAC (Gaurav & Singh, 2020). In the present study, the yield stress of steel bars will be taken into account as a parameter included in the empirical relationship adding to the other parameters.

For verifying the applicability of the empirical relations proposed for traditional concrete to recycled aggregate concrete, the previous empirical relations were employed to calculate the bond stress, and the results were compared with the experimental results of the present study as shown in (Fig. 4). It can be seen from (Fig. 4) regarding the big differences between empirical and experimental bond stresses, that the empirical relations for bond stress established for traditional concrete cannot be directly applied to recycled aggregate concrete (RAC) due to the inherent differences in properties and behavior. On the other hand, the bond stresses obtained from the relation proposed for recycled aggregate concrete (Seara-Paz et al., 2014; Kim et al., 2015), are closer to the experimental values, (see Fig. 4). However, those relationships were obtained depending on the limited number of specimens.

Fig. 4 compares the empirical bond stress predictions with the experimental bond stress values obtained in the present study. The results indicate that all of the considered empirical models underestimate the bond stress. Specifically, the ratio of experimental bond stress to the bond stress predicted by the CEB-FIB model ranges from 1.9 to 3.0, while the Australian Standard yields ratios between 2.0 and 3.0. The ACI model provides closer predictions, with ratios ranging from 1.12 to 1.8. Similarly, the models proposed by Orangun and Darwin produce ratios between 1.2 and 1.9, and 1.2 and 1.8, respectively. Among the evaluated models, the equation proposed by Kim et al. shows the best agreement with the experimental results, with ratios ranging from 1.1 to 1.7, although it still consistently underestimates the bond stress.

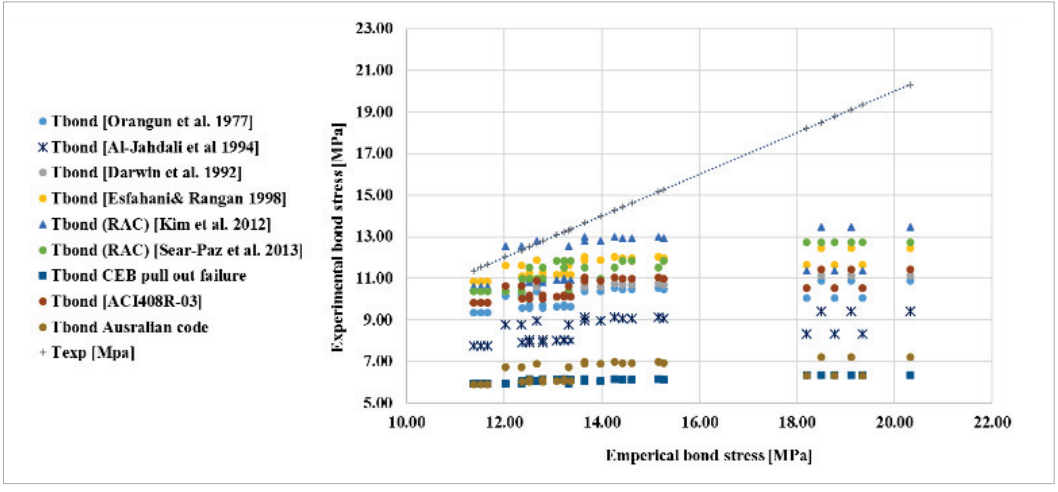


Fig. 4

Comparison between empirical bond stress and experimental bond stress of the present study

The observed discrepancies highlight the limitations of existing empirical equations in accurately predicting the bond strength of recycled aggregate concrete (RAC). Most of these equations were developed using relatively limited experimental datasets generated by the respective authors under specific material properties and testing conditions, which restricts their general applicability. This emphasizes the need for a new empirical bond stress model derived from a large and diverse experimental database that incorporates results from multiple independent studies covering a wide range of concrete strengths, recycled aggregate replacement ratios, reinforcement details, and specimen geometries. Such a comprehensive database enables the development of a more robust and reliable predictive equation with improved accuracy and broader applicability for engineering design.

In this study, new empirical relationships were proposed using 175 points from previous studies, depending on six input parameters. Table 5 represents the adopted references and the range of the variables. Six input parameters were included, which are the most important parameters that affect the bond stress and were found in the previous studies and adopted in the empirical bond relations. The inputs are: $\sqrt{F'_c}, \frac{C_c}{d_b}, \frac{d_b}{l_b}, R, \frac{W}{C}, A_s. F_y.$, where F'_c is the compressive strength of concrete, C_c is the concrete cover of the pull-out specimen, d_b the diameter of the steel bar, l_b the bond length of the steel bar, R: R∈[0→1], the replacement ratio of recycled aggregates with natural aggregates, $\frac{W}{C}$ the water-to-cement ratio, A_s the area of steel bar, and F_y is the yield stress.

Table 5

The range of variables from the adopted research

Authors							R		W/C		AS*F_Y		τexp [Mpa]	
	max	min	max	min	max	min	max	min	max	min	max	Min	max	min
(Xiao & Falkner, 2007)	5.79	5.20	4.50	4.50	0.20	0.20	0	1	0.43	0.43	31400	31400	17.39	15.60
(Wardeh et al., 2017)	6.44	5.47	5.00	4.08	0.20	0.10	0	1	0.93	0.82	56520	39250	17.40	11.10
(Prince & Singh, 2014)	6.08	4.90	5.75	1.50	0.20	0.20	0	1	0.54	0.54	245313	25120	23.95	8.10
(Seara-Paz et al., 2014)	7.31	5.93	4.50	4.50	0.20	0.20	0	1	0.65	0.50	39250	39250	15.60	9.06
(Kim et al., 2015)	6.64	5.15	4.19	4.19	0.25	0.25	0	1	0.51	0.33	86011	86011	29.92	17.65
(Abdulazeez et al., 2021)	7.07	3.87	5.75	2.50	0.20	0.08	0	1	0.55	0.51	257578	36738	22.70	4.90
(Bravo et al., 2021)	7.36	5.50	4.50	4.50	0.12	0.12	0	1	0.64	0.52	56520	56520	16.30	9.50
(Guerra et al., 2014)	7.02	6.59	7.83	5.75	0.20	0.07	0	1	0.52	0.52	106907	62262	15.34	5.98
(Breccolotti et al., 2013)	7.46	6.04	6.60	6.60	0.09	0.09	0	1	0.50	0.45	69237	69237	25.90	20.10
(Choi & Kang, 2008)	6.16	4.77	4.18	4.18	0.11	0.11	0	1	0.50	0.40	160768	160768	15.98	11.58
(Reis et al., 2009)	5.70	5.60	4.50	7.50	0.20	0.20	0	0.5	0.25	0.50	62800	62800	10.81	15.71
(Huang & Wang, 2011)	6.07	5.04	2.60	2.60	0.20	0.08	0	1	0.47	0.47	90834	90834	19.00	9.30
(Rafi, 2018)	5.70	5.00	7.83	4.50	0.20	0.20	0.1	0.3	0.50	0.50	132822	52111	26.30	19.20
(Shang et al., 2017)	5.20	5.20	4.80	2.90	0.20	0.20	1	1	0.56	0.56	151976	61544	14.80	10.00

The selection of the input variables was based on both previous research and statistical evaluation of the compiled database. Parameters such as concrete compressive strength, concrete cover, bar diameter, embedment length, and recycled aggregate replacement ratio have been widely recognized in the literature as the primary factors governing steel–concrete bond behavior and are commonly incorporated into empirical bond models. Although the water-to-cement (W/C) ratio is correlated with concrete compressive strength, some studies have shown that it also influences bond behavior through its effect on the porosity and quality of the interfacial transition zone (ITZ), resulting in different bond performances even for concretes with similar compressive strengths (Kim et al., 2015, 2017). Therefore, the W/C ratio was retained as an independent

variable. Similarly, the parameter ($A_s \cdot F_y$) was included because several analytical and empirical bond formulations consider reinforcement characteristics in describing the force transfer between steel and concrete (ACI Committee 408, 2003; CEB, 1977; fib, 2000; Filippou et al., 1983; Harajli, 2007; Lowes et al., 2004; Vembu & Ammasi, 2023). In the present study, the inclusion of the parameter ($A_s \cdot F_y$) an water to cement ratio (W/C) improved the predictive capability of the empirical relationship by reducing the prediction error and increasing the correlation between the predicted and experimental bond strengths. The regression analysis demonstrated that this parameter contributed significantly to the overall performance of the model, indicating that reinforcement characteristics represented within the compiled database have a measurable influence on the empirical prediction of bond behavior.

The **equation 1** represents the proposed equation, where seven coefficients $X_1 \rightarrow X_7$ will be found by minimizing the differences between the experimental and empirical bond stresses.

$$\tau_{bond} = X_1 + X_2 . \sqrt{F'_c} + X_3 . \left(\frac{C_c}{d_b}\right) + X_4 . \frac{d_b}{l_b} + X_5 . (R) + X_6 . \frac{w}{c} + X_7 . A_s . \quad (1)$$

The coefficients ($X_1 \rightarrow X_7$) were determined using CurveExpert software through linear regression by minimizing the mean squared error between the experimental and predicted bond stresses. When the regression analysis was performed using the complete database of 175 experimental results, the resulting correlation coefficient was only 0.61, indicating that a single empirical equation could not adequately represent the bond behavior over the full range of concrete compressive strengths. Therefore, the database was divided into four compressive-strength intervals (F'_c<25 MPa, 25≤F'_c≤30 MPa, 30<F'_c<40 MPa, and F'_c≥40 MPa), and separate regression equations were developed for each interval using **Equation (1)**. The resulting coefficients and corresponding correlation factors are presented in **Table 6**.

The comparison between the experimental bond stress and the empirical bond stresses from the proposed empirical equations are presented in (**Fig. 5**, **Fig. 6**, **Fig. 7** and **Fig. 8**). It can be noticed that the performance of the proposed equations give better results reliable with a correlation factor between 0.72 and 0.91 than the old empirical equations presented in the literature and shown in (**Fig. 4**).

The comparison between the empirical bond stress and the experimental bond stress in the present study presented in (**Fig. 9**) shows that the proposed relations are reliable with a correlation factor 0.64. However, empirical methods include limitations in accuracy and flexibility compared to the ANN method, which offers improved predictive capabilities and adaptability (Barbosa & Ribeiro, 2016).

Table 6
The parameters of empirical equation (1)

F'_c[MPa]	X_1	X_2	X_3	X_4	X_5	X_6	X_7	Correlation Factor
F'_c<25	-36.44	1.50	2.87	34.19	-1.22	-0.00047	-0.002	0.84
25≤F'_c≤30	-8.22	3.90	1.15	32.26	-4.89	-8.22	-7.2×10^{-6}	0.72
F'_c[30-40]	-46.19	4.38	4.07	49.92	0.35	4.03	0.000079	0.86
F'_c≥40	61.35	-3.43	-0.67	25.40	-1.80	-42.20	-0.000023	0.91

It should be noted that the proposed equations are interval-specific empirical relationships. Since different regression coefficients are used for different compressive strength ranges, small discontinuities may occur near the interval boundaries. Therefore, the equations should be applied only within their corresponding strength ranges. The ANN model does not exhibit this limitation and provides continuous predictions over the entire parameter domain.

Fig. 5

The comparison between the experimental and the proposed empirical bond stress for F'_c<25 MPa.

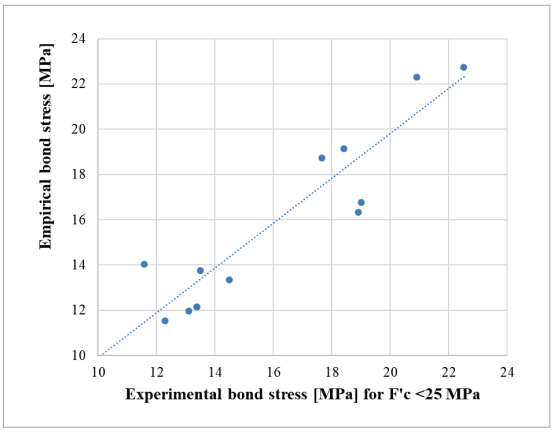


Fig.6

The comparison between the experimental and the proposed empirical bond stress for 25≤F'_c≤30 MPa.

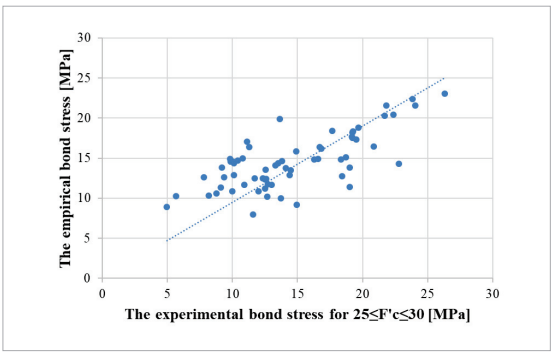


Fig.7

The comparison between the experimental and the proposed empirical bond stress for F'_c ∈ [30-40].

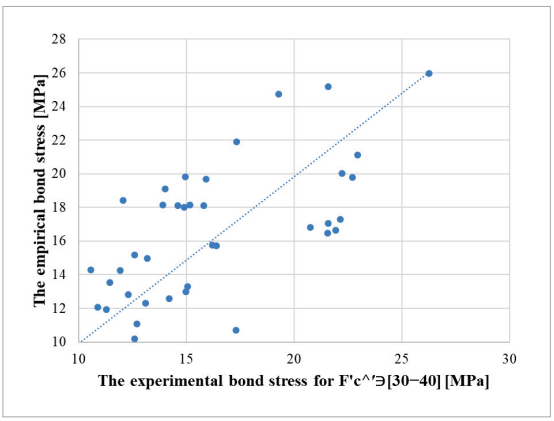
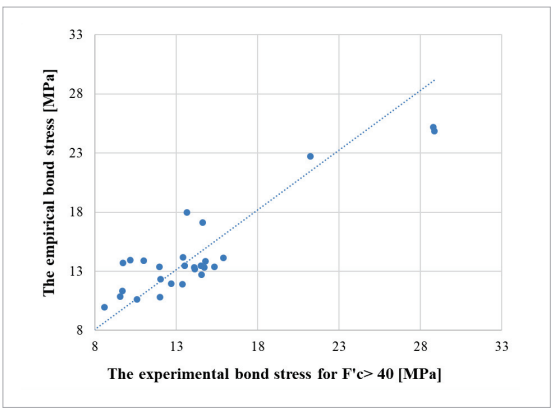


Fig.8

The comparison between the experimental and the proposed empirical bond stress for F'_c>40 MPa.



Proposing an artificial neural network model in the present study

Artificial intelligence (AI), particularly artificial neural networks (ANNs), has revolutionized the prediction of material properties in concrete and recycled aggregate concrete (RAC), and offers superior accuracy and efficiency compared to traditional models (Lee, 2003; Alsaleh et al., 2023).

The machine learning framework developed in this study is based on a comprehensive dataset of pull-out tests investigating the bond behavior between steel reinforcement and recycled aggregate concrete (RAC). The compiled dataset consists of a total of 205 experimental data points, including 175 results collected from previously published studies and 30 pull-out test results obtained from the experimental program conducted in the present research. The literature-based data were used exclusively for training the model, while the experimental results of the present study were reserved for independent validation to ensure unbiased assessment of model performance.

The input parameters were selected based on their established mechanical relevance to bond behavior and their frequent appearance in existing empirical models. The same six input parameters that were adopted in proposing the empirical relations are adopted for the ANN model for steel RAC bond stress. These parameters include the square root of concrete compressive strength $\sqrt{(F'_c)}$, the ratio of concrete cover to bar diameter (C_c/d_b), the ratio of bar diameter to bond length (d_b/l_b), the recycled aggregate replacement ratio (R), the water-to-cement ratio (W/C), and the product of steel bar area and yield strength ($A_s \cdot F_y$). The output variable of the model is the maximum bond stress obtained from pull-out testing. The ranges of all input variables were defined based on experimental evidence reported in the literature and are

summarized in **Table 5**. The following formula can be used to express the relationship between the inputs (x_i) and the output (y) in the ANN:

$$y = F(S) = F(b + \sum_{i=1}^{n} w_i . x_i) \quad (2)$$

x_i: Input data, w_i: The weight of the neural model, b: The bias, S: The activity.

The transfer function was (RELU) (Rectified Linear Activation Function), which is a powerful activation function in deep neural networks, providing crucial non-linear properties for training and enhancing the performance of ANN. The function is represented mathematically as follows:

$$f(x) = \max(0, x) \quad (3)$$

$$\text{Mean} = \bar{x} = \frac{\text{Sum of all data point}}{\text{Number of data point}} \quad (4)$$

The information transmission between neurons is controlled by trainable weights and biases. During training, the input data are first propagated forward through the network to obtain the predicted bond stress. The prediction error is then quantified using the mean squared error (MSE) loss function. Gradients of the loss function with respect to the network weights and biases are calculated using the back-propagation algorithm. This forward-propagation, loss-calculation, back-propagation, and parameter-update process is repeated over successive training epochs until the stopping criterion is reached. During inference (prediction), the trained weights and biases are kept fixed, and only forward propagation is performed to obtain the predicted bond stress. Therefore, no weight updating or back-propagation is performed during inference. The input variables are normalized before being introduced to ANN, and the mean of the collected data is calculated by the following equation:

$$\text{Variance} = \frac{\sum(x_i - \bar{x})^2}{n-1} \quad (5)$$

For every variable in the input variables, the standard scalar is calculated:

$$\text{standard scalar} = \frac{x_i - \bar{x}}{\text{standard deviation}} \quad (6)$$

$$T_{bond} = \text{Bias}_{outputlayer} + \sum_{i=1}^{n} w_1 . F(T_x) \quad (7)$$

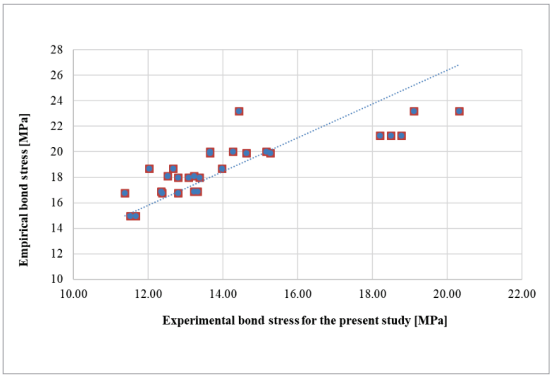


Fig. 9
The comparison between the proposed empirical and the experimental bond stress for the present study.

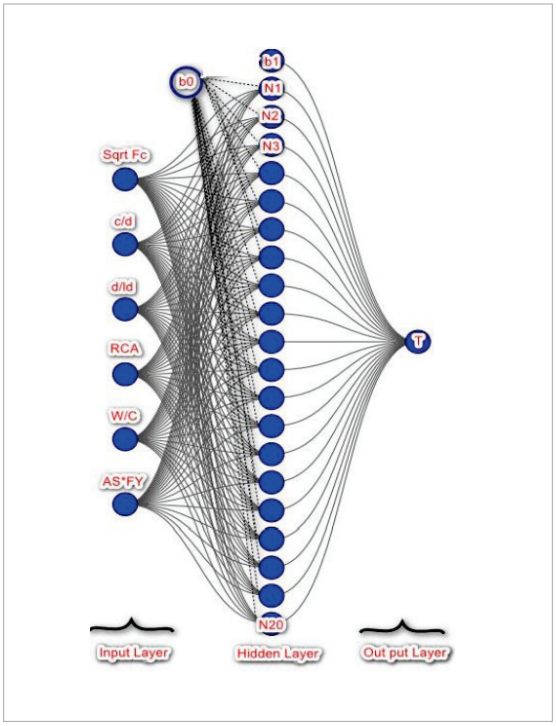


Fig. 10
ANN model of the present study

$Bias_{output\ layer}$: Which is 0.61, for the given data, w_1: Layer weight matrix, $F(T_x)$: RELU function. The following final numbers were acquired and used to calculate the bond stress:

$$T_x = \begin{bmatrix} 0.8608 & 0.8902 & -0.1319 & -0.9823 & -1.0190 & 0.3453 \\ -1.0623 & -0.7197 & 0.7252 & 0.6530 & 0.0692 & 0.2542 \\ 0.1980 & -0.2413 & -0.0638 & -0.1908 & 0.0364 & -0.1750 \\ 0.3952 & 0.4207 & -0.3150 & -0.7004 & -1.1919 & 0.6845 \\ 0.3244 & 0.3471 & -0.4392 & 0.2539 & 0.8619 & -1.3102 \\ 0.4338 & -1.1082 & 0.4548 & -0.7654 & -1.0991 & 0.8496 \\ 0.0292 & 0.7506 & -0.1576 & 0.2837 & -0.9382 & 0.3416 \\ -0.6711 & 0.3062 & 0.9778 & -0.2566 & -0.3770 & -1.0752 \\ -0.5526 & -0.0056 & 0.5330 & -0.8427 & 0.4590 & -0.2815 \\ 0.0597 & -0.2309 & -0.0520 & 0.0115 & 0.0076 & -0.0290 \\ 0.1164 & -0.1657 & 0.0245 & -0.0504 & 0.1273 & 0.1866 \\ 0.9310 & -0.9090 & -0.7450 & 1.0210 & 0.2843 & 0.4837 \\ -0.0559 & 0.1003 & 0.0276 & 0.0515 & -0.1413 & -0.0026 \\ -0.1148 & 0.1909 & -0.1217 & -0.0211 & -0.0172 & 0.1153 \\ 0.1957 & -0.0899 & 0.1398 & 0.0815 & 0.0380 & 0.2711 \\ 0.5099 & -0.0828 & 0.1823 & 0.1421 & 0.4097 & 0.2047 \\ -0.0413 & -0.1874 & -0.3211 & 0.0249 & -0.0816 & 0.0094 \\ -0.7814 & 0.0413 & 1.1060 & -0.7221 & 0.4940 & -0.8614 \\ 0.0741 & 0.3767 & 0.5429 & -0.1104 & 0.1308 & -0.3639 \\ 0.1066 & 0.1669 & -0.1509 & -0.2544 & -0.1007 & -0.0828 \end{bmatrix} X \begin{bmatrix} \left(\frac{\sqrt{F_c'}-\bar{X}}{variance}\right) \\ \left(\frac{\frac{c}{d}-\bar{X}}{variance}\right) \\ \left(\frac{\frac{d}{l_d}-\bar{X}}{variance}\right) \\ \left(\frac{RCA-\bar{X}}{variance}\right) \\ \left(\frac{\frac{w}{c}-\bar{X}}{variance}\right) \\ \left(\frac{(A_S X F_Y)-\bar{X}}{variance}\right) \end{bmatrix} + \begin{bmatrix} 0.8915 \\ 0.8092 \\ -0.2095 \\ 0.8281 \\ 0.9654 \\ 1.0327 \\ 0.774 \\ 0.7996 \\ 0.6281 \\ -0.2082 \\ -0.3028 \\ 1.0064 \\ -0.2439 \\ -0.3016 \\ -0.2901 \\ -0.0509 \\ -0.1695 \\ 0.8136 \\ 0.1242 \\ -0.2237 \end{bmatrix} = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \\ T_7 \\ T_8 \\ T_9 \\ T_{10} \\ T_{11} \\ T_{12} \\ T_{13} \\ T_{14} \\ T_{15} \\ T_{16} \\ T_{17} \\ T_{18} \\ T_{19} \\ T_{20} \end{bmatrix}, W_1 = \begin{bmatrix} 0.89470 \\ 1.22383 \\ 0.0244 \\ 1.02030 \\ 0.90210 \\ 0.79401 \\ 0.64419 \\ 1.39097 \\ 0.67541 \\ -0.08521 \\ -0.24857 \\ 0.78186 \\ -0.26261 \\ -0.12365 \\ -0.16338 \\ 0.15799 \\ 0.06196 \\ 1.20751 \\ 0.28541 \\ 0.01610 \end{bmatrix} \quad (8)$$

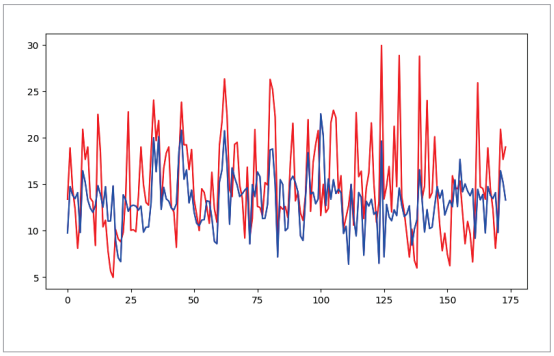


Fig. 11

Comparison between experimental bond stress (red line) and ANN bond (blue line) in the training process.

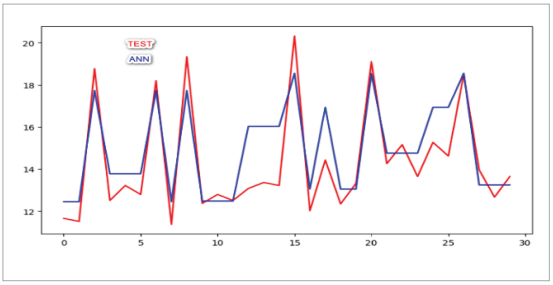


Fig. 12

Comparison between experimental bond stress (red line) and ANN bond stress (blue line) in the verification process.

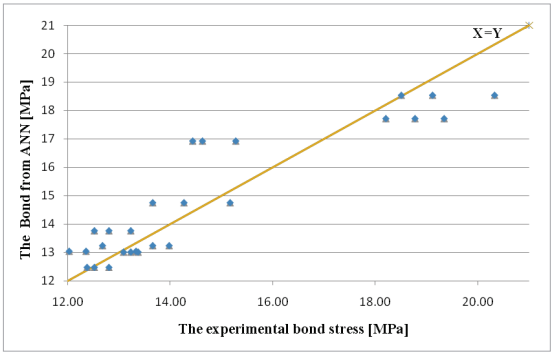


Fig. 13

A comparison between the experimental and ANN bond stresses

The artificial neural network (ANN) model was developed using Python in the Google Colaboratory environment, employing standard deep learning libraries. The network architecture consists of an input layer with six neurons corresponding to the selected input parameters, one hidden layer with 20 neurons, and a single output neuron representing bond stress, (see Fig. 10).

A batch size of 10 was adopted, and the model was trained for up to 1000 epochs. To reduce the risk of overfitting, an early stopping strategy was implemented based on the validation loss, terminating the training process when no further improvement was observed for 50 consecutive epochs. The model achieved a training MSE training of 0.133 and a validation/test MSE test of 0.0095, demonstrating satisfactory predictive accuracy and generalization performance.

Fig. 11 represents the comparison between experimental bond stress and ANN bond in the training process. The validation process confirmed the model's robustness, yielding a mean error of 7.6%. The strong agreement between the experimental and predicted bond stresses is visualized in (Fig. 12) which is the

correlation figure and (Fig. 13) the comparative Figure. The Comparison between correlation numbers of empirical equations and ANN model is presented in (Table 7).

Table 7
Comparison between correlation numbers of empirical equations and ANN model

Model	Correlation Coefficient (R)
Empirical Equation	0.68–0.91
ANN	0.98

The choice between empirical relations and Artificial Neural Networks (ANNs) for predicting the properties of recycled aggregate concrete involves a trade-off between simplicity and accuracy. Empirical methods are advantageous due to their straightforward interpretability, lower computational demands, and ease of implementation (Khademi et al., 2021; Cakiroglu et al., 2023; Peng et al., 2023). However, their major drawback is limited predictive accuracy. ANNs, on the other hand, address this limitation by effectively modeling complex data interactions. Unlike empirical models, which rely on predefined functional forms, the ANN captures complex nonlinear interactions among input variables, allowing it to adapt to the inherent variability of recycled aggregate concrete. This capability results in significantly higher reliability and precision, as evidenced by correlation coefficients nearing 1.0 and reduced errors, establishing ANNs as a superior tool for critical predictions such as bond strength between steel and RAC. These findings confirm that the ANN model provides a robust predictive framework for estimating steel–RAC bond stress within the investigated parameter ranges.

The proposed machine learning framework contributes to sustainable construction by facilitating the reliable use of recycled aggregate concrete in reinforced structural applications. By reducing dependence on extensive experimental testing, the ANN model enables rapid evaluation of bond performance across a wide range of material compositions, thereby lowering material consumption, experimental cost, and associated environmental impact.

Moreover, the ability to accurately predict bond stress enhances confidence in the structural application of RAC, promoting higher replacement ratios of natural aggregates and supporting circular economy principles. The integration of machine learning into material modeling thus represents an effective tool for accelerating the adoption of sustainable construction materials.

Conclusion

This study investigated the bond behavior between steel reinforcement and recycled aggregate concrete (RAC) through experimental testing and predictive modeling. Thirty pull-out tests were conducted using two bar diameters (14 and 16 mm) and five recycled aggregate replacement ratios (0%, 25%, 50%, 75%, and 100%).

The experimental results showed that increasing the recycled aggregate replacement ratio reduced both compressive strength and bond stress. The compressive strength decreased by up to 13.1%, while the bond stress decreased by 23.5–34.9% for the 14 mm bars and by 29.5–38.6% for the 16 mm bars. Increasing the bar diameter from 14 mm to 16 mm also reduced the bond stress by approximately 2.8%.

Using a database of 175 experimental results collected from the literature, four empirical equations were developed for different compressive-strength intervals. The proposed equations showed improved agreement with the experimental data compared with existing bond-stress formulations, achieving correlation coefficients ranging from 0.72 to 0.91.

An Artificial Neural Network (ANN) model was developed and validated using the same governing parameters adopted in the empirical formulations. The ANN model demonstrated superior predictive performance, achieving a correlation coefficient of 0.98 and a mean squared error of 0.0095 on the validation dataset.

The comparison between the empirical equations and the ANN model indicates that the ANN approach provides more accurate predictions of bond stress for steel-reinforced RAC within the investigated parameter ranges. Therefore, the proposed ANN model can be considered a reliable predictive tool for estimating bond stress under conditions similar to those considered in this study.

Limitations and Future Research

Despite the strong performance of the proposed ANN model, certain limitations should be acknowledged as the applicability of the model is restricted to the parameter ranges covered by the training data. Future research should focus on expanding the dataset to include beam-level bond tests, cyclic loading conditions, and different surface treatments of recycled aggregates.

Use of Artificial Intelligence Tools

The authors used an artificial intelligence (AI) tool solely for language editing, including grammar checking, improving sentence structure, and rephrasing selected sentences for clarity and readability. The AI tool was not used to generate scientific content, analyze data, interpret results, or draw conclusions. The authors reviewed and approved all AI-assisted edits and take full responsibility for the content and accuracy of the manuscript.

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