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RESEARCH ARTICLE

Shear strength assessment of reinforced recycled aggregate concrete beams without stirrups using soft computing techniques

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Abstract
This paper presents a study to predict the shear strength of reinforced recycled aggregate concrete beams without stirrups using soft computing techniques. The methodology involves the development of a Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression (MOGA-EPR) and Gene Expression Programming (GEP) models. The input variables considered are the longitudinal reinforcement ratio, recycled coarse aggregate ratio, beam cross-section dimensions, and concrete compressive strength. Data collected from the literature were used to train and validate the models. The results showed that the MOGA-EPR and GEP models can accurately predict the shear strength of beams without stirrups. The models also performed better than equations from the codes and literature. This study provides an alternative approach to accurately predict the shear strength of reinforced recycled aggregate concrete beams without stirrups.

Keywords Shear strength of reinforced concrete · Recycled aggregate concrete · Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression · Gene expression programming · Soft computing

Abbreviations

a/d	Shear span-to-effective depth ratio
b	Beam width
CDW	Construction and Demolition Waste
d	Beam effective depth
d_{max}	Maximum aggregate size
GA	Genetic Algorithm
GEP	Gene Expression Programming
MAE	Mean Absolute Error
MOGA-EPR	Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression
NCAC	Natural Coarse Aggregate Concrete
RAC	Recycled Aggregate Concrete
RC	Reinforced Concrete
RCA	Recycled Coarse Aggregate
RMSE	Root Mean Squared Error
STDV	Standard Deviation
V_c	Shear force of concrete
$V_{c,\ experimental}$	Shear force of concrete measured experimentally
$V_{c,\ p}$	Predicted Shear force of concrete measured by an equation
ρ_w	Longitudinal reinforcement ratio
f_c	Compressive strength of concrete
μ	Mean
n	Number of data points
R^2	Coefficient of determination

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1 Introduction

Concrete is the most popular material employed in construction around the world. The demolition of old structures and the construction of new ones leads to an increased accumulation of Construction and Demolition Waste (CDW), causing environmental issues. Moreover, producing new concrete involves utilizing non-renewable resources like cement and natural coarse aggregates. To cope with this, various studies have been conducted on recycling CDW to reduce the demand for natural resources and cut down on construction waste [1–4]. As concrete is the largest source of CDW, many research studies have examined the use of Recycled Coarse Aggregate (RCA) to produce Recycled Aggregate Concrete (RAC) and assess its mechanical properties and durability in comparison to those of Natural Coarse Aggregate Concrete (NCAC) [5–7] given that coarse aggregate makes up 60–75% of the volume of concrete. Nevertheless, test results have been discouraging as concrete with RCA has demonstrated inferior properties compared to concrete with NCAC [5–8].

RCA is created by crushing concrete debris that is 90 to 95% of the total mass and has a contamination level at or below 1%. This aggregate is taken from demolition waste that is clean and free of any sound [9, 10].

Recently, recycled aggregate obtained from construction and demolition waste has been gaining considerable attention, due to its potential use in green concrete structures. Many countries have been motivated to substitute natural aggregates with recycled aggregate in the creation of concrete, due to the shortage of natural aggregates, rising transportation expenses, limited dumping sites, and environmental contamination. Consequently, numerous studies have been conducted to ascertain how waste can be employed in the construction industry [11].

Despite a great deal of research being done to examine the rheology and durability of recycled aggregate, only a few studies have looked into the behavior of recycled aggregate concrete structural members [12–15]. These studies are particularly important, as it is hard to make predictions about the performance of reinforced recycled aggregate concrete members based solely on the tests done on the material characteristics of the recycled aggregate [16].

Analysis of current design equations by simply comparing them with experimental data may lead to inaccurate results because the gathered information may include incorrect data [17]. The research [18] suggests a Bayesian method to evaluate various shear prediction models of RAC beams. This Bayesian parameter estimation eliminates the fragility of any conclusion obtained from the traits of the collected data. The risk of wrong results is minimized by employing Bayesian parameter estimation, as it provides a full distribution of believable values in terms of mean, standard deviation, and the effect size of experimental-to-calculated capacity values.

Muttoni and Ruiz [19] have discussed critical shear crack width theory, including developing and activating the arching action in reinforced concrete beams subjected to shear. The critical shear crack, which can be taken regarding the effective depth of the reinforcements (d), is identified as one parameter that governs the shear strength, along with its location, width, and aggregate size.

From what can be gathered from the previous literature on the shear capacity of RAC beams, it is clear that a more comprehensive analysis is required to confirm whether or not existing design codes are accurate in their predictions. Although the code equations may be overly conservative in their predictions of the shear capacity of RAC beams, it is essential to accurately determine the degree of this conservatism for further safety and reliability of the shear design of these beams [18].

The shear strength of reinforced recycled aggregate concrete beams without stirrups is of great importance as it directly affects the structural integrity of the beam. Without stirrups, the beam is more vulnerable to failure, potentially leading to a collapse which can have serious consequences for the building and its occupants. Investigating shear strength helps to ensure that the beam can withstand the loads and forces of the environment and execute its function successfully. However, the shear strength of concrete is a very intricate phenomenon that cannot be simply deduced from the properties of the elements used [20]. Research has been done to find replacements for natural aggregates, including coal bottom ash, waste glass, waste marble powder, and other items [21–23].

This study particularly looks into replacing natural aggregates with recycled aggregates from demolition waste and assessing the shear strength of the reinforced concrete members. As shear strength is a complex matter and there is limited research on the use of recycled aggregates theoretically, more in-depth investigation into using RA in concrete structures is necessary.

This research is exploring the influence of different parameters and ranges on the shear force of concrete (V_c) beams made with coarse recycled aggregate (RCA) from demolition waste. It will contribute new information and data to the existing body of knowledge on the topic, assisting developers of structural codes in formulating equations for predicting shear strength in recycled concrete. In an age where large data sets are highly valued, more records are essential for refining construction codes that promote sustainable materials, particularly for complicated behaviour based on empirical evidence [20].

Machine Learning (ML) has gained popularity in the field of engineering due to its ability to establish connections between input and output data [24–30]. In recent studies [24, 26–29], ML techniques like Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression (MOGA-EPR), Genetic Expression Programming (GEP), Multivariate Adaptive Regression Splines (MARS), Model Tree (MT), and Extreme Learning Machine (ELM) have been employed to explore the mechanical properties and durability of concrete. These methods are utilized for predicting the behavior of concrete materials [24–30].

This paper investigates the shear strength of coarse recycled aggregate (RCA) beams without stirrups. Understanding that RCA affects the shear strength is an important factor to consider in the design toward the net-zero policy. Reference [31] studied the effect of the RCA substitution rate and the longitudinal reinforcement ratio (ρ_w) on the V_c of the beams. Five different substitution levels (0%, 25%, 50%, 75%, and 100%) and two reinforcement ratio percentages (1.16% and 1.81%) were selected for the study. Two NCAC beams and eight RAC beams without stirrups were tested on one-third of the beam span as described in the experimental work of reference [31]. The results of RCA beams without stirrups from other studies were also compiled and evaluated to evaluate the accuracy of the existing equations.

Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression (MOGA-EPR) and Gene Expression Programming (GEP) are powerful computational tools, that are especially useful in estimating concrete strength [24, 25]. MOGA-EPR uncovers the relationships between physical input variables crucial to determining shear strength in this particular concrete by applying the genetic algorithm (GA) to regression analysis. This method outperforms classic regression algorithms by eliminating overfitting problems, resulting in more accurate and dependable predictions. Engineers and researchers can use MOGA-EPR to adjust the correlation structure, exponent ranges, and term numbers to the particular properties of recycled aggregate concrete, allowing for improved design and construction decisions for long-term infrastructure projects.

2 Current code provision for shear in the beam without stirrups

In this paper, a comprehensive empirical evaluation was carried out to predict the shear strength of concrete members without stirrups. The findings of prior research show that the shear capacity of reinforced concrete (RC) beams is lowered when natural aggregate is replaced with recycled aggregate [12, 15, 32]. To see if the shear capacity prediction equations outlined in Table 1 are suitable for use when designing RAC beams, they need to be tested against experimental results. Therefore, further evaluation is necessary.

The ACI 318-14 [33], ACI 318-19 [34], Eurocode 2 [35], Indian Standard:456 [36], and the equation proposed by Bazant and Yu [37, 38] consider the longitudinal reinforcement ratio (ρ_w), compressive strength of concrete (f_c), and the beam effective depth (d) when predicting the shear capacity of RC beams. Furthermore, CEB-FIP [39], Zsutty [40, 41], Niwa et al. [42], Gastebled and May [43], Kim and Park [44], Rebeiz [45], New Zealand code [46], and Arslan [47] include the shear span-to-depth ratio (l/d) in their models. Bazant and Sun [48] and Bazant and Kim [49] developed their equations based on the fracture mechanics approach, accounting for the compressive strength of concrete, longitudinal reinforcement ratio, the effective depth of the beam, and shear span-to-depth ratio. Russo et al. [50] and Pradhan et al. [51] also consider these parameters, but Rahal and Alrefaei [52], the modified ACI 318-19 and Pradhan et al. [51] are the only ones from the literature include the aggregate replacement ratio (RCA) and maximum aggregate size (d_{max}.).

In this article, the 18 equations in Table 1 will be examined with the Gene Expression Programming (GEP) and Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression (MOGA-EPR) models that have been developed and various statistical and numerical contrasts will be highlighted and discussed later on in the article.

3 Methodology

This paper investigates the potential of predicting the shear force of concrete (V_c) beams without stirrups, using machine learning techniques. To do this, experimental datasets were gathered based on reference [31], and the values of the shear force of concrete were calculated according to Eqs. (1) to (18) listed in Table 1, using the following input variables; the percentage of RCA replacement ratio, compressive strength (f_c), effective depth (d), beam width (b), shear span-to-effective depth ratio (a/d), and longitudinal reinforcement ratio (ρ_w). Three models employing GEP and MOGA-EPR machine learning techniques were used to estimate the shear force of the concrete beams without stirrups with different RCA percentages.

The procedure outlined in Fig. 1 is the approach adopted in this paper for determining the shear force of concrete (V_c) beams without stirrups. It begins with collecting and analyzing the data statistically from reference [31], which is used to form GEP and MOGA-EPS models and create various equations that predict the shear force of concrete. Following this, data grouping for training and testing the predicted equations, then the statistical indicators for the data are computed. Subsequently, the results from the models are compared to existing equations (in Table 1).

3.1 Data collection and statistical analysis

A comprehensive experimental shear database was collected to assess the accuracy of the equations in Table 1 and to formulate models from the GEP and MOGA-EPR methods for predicting the concrete shear strength of RAC beams. The compilation comprises 128 results from RAC beams tested by other researchers [12–15, 32, 44, 51, 52, 54–62]. The parameters taken into account during this investigation were the percentage of RCA replacement

Table 1 The current code equations for the shear force of concrete members without stirrups

#	Reference	Equation of V_c (kN)	Equation #
1	ACI 318-14 [33]	$V_c = 0.17 \times \sqrt{f_c} \times b \times d$	Eq. (1)
2	ACI 318-19 [34]	$V_c = 0.66 \times \lambda s \times \rho_w^{1/3} \times \sqrt{f_c} \times b \times d$ $\lambda_s = \sqrt{\frac{2}{1+0.004\times d}} \leq 1.0$	Eq. (2)
3	Rahal and Alrefaei [52]	$V_c = 0.17 \times \lambda_d \times \lambda_R \times \sqrt{f_c} \times b \times d$ λ_d is the reduction factor for lightweight aggregate λ_R = 0.8 concrete with RCA and 1.0 concrete with NCA	Eq. (3)
4	ACI 318-19 Modified [31]	$V_c = 0.66 \times \lambda_s \times \lambda_d \times \beta_r \times \rho_w^{1/3} \times \sqrt{f_c} \times b \times d$ 50% ≥ RCA ratio ≥ 100% β_r= 0.75; Otherwise β_r= 0.9	Eq. (4)
5	Eurocode 2 [35]	$V_c = 0.18 \times \left(1 + \sqrt{\frac{200}{d}}\right) \times \left(\rho_w \times f_c\right)^{1/3}$	Eq. (5)
6	New Zealand code [46]	$V_c = \left(0.07 + \left(10 \times \rho_w\right)\right) \times \sqrt{f_c}$	Eq. (6)
7	CEB-FIP [39]	$V_c = 0.15 \times \left(1 + \sqrt{\frac{200}{d}}\right) \times \left(\frac{3}{a/d}\right)^{1/3} \times \left(\rho_w \times f_c\right)^{1/3}$	Eq. (7)
8	Indian Standard:456 [36]	$V_c = \frac{0.85\times\sqrt{f_{c,cube}}\times\left(\sqrt{1+(5\times\beta)}-1\right)}{6\times\beta}; \beta = \frac{0.8\times f_{c,cube}}{6.89\times\rho_w}$	Eq. (8)
9	Niwa et al. [42]	$V_c = 1.125 \times fc1/3 \times \rho_w^{1/3} \times \left(\frac{1}{d}\right)^{0.25} \times \left(0.75 + 1.4 \times a/d\right)$	Eq. (9)
10	Gastebled and May [43]	$V_c = 0.15 \times \frac{37.41}{\sqrt{d}} \times \left(\frac{3}{a/d}\right)^{1/3} \times \left(100 \times \rho_w\right)^{1/6} \times \left(1 - \sqrt{\rho_w}\right)^{2/3} \times f_c^{0.35}$	Eq. (10)
11	Kim and Park [53]	$V_c = 0.13.55 \times f_c^{1/3} \times \rho_w^{3/8} \times \left(0.4 + \frac{1}{a/d}\right) \times \left(\frac{1}{\sqrt{1+0.008\times d}} + 0.18\right)$	Eq. (11)
12	Bazant and Yu [37, 38]	$V_c = 3.5 \times \sqrt{\frac{f_c\times\rho_w^{2/3}}{d}}$	Eq. (12)
13	Zsutty [40, 41]	$Vc = 2.21 \times \left(\frac{\rho_w\times f_c}{a/d}\right)^{1/3} \times \left(\frac{2.5}{a/d}\right); a/d < 2.5$ $Vc = 2.21 \times \left(\frac{\rho_w\times f_c}{a/d}\right)^{1/3}; a/d \geq 2.5$	Eq. (13)
14	Arslan [47]	$V_c = \left(0.15 \times \sqrt{f_c} + 0.02 \times fc^{0.65}\right) \times \left(\frac{2.5}{a/d}\right); a/d < 2.5$ $V_c = \left(0.15 \times \sqrt{f_c} + 0.02 \times fc^{0.65}\right); a/d \geq 2.5$	Eq. (14)
15	Rebeiz [45]	$V_c = 0.4 + \sqrt{f_c \times \frac{\rho_w}{a/d}} \times \left(2.7 - 0.4 \times a/d\right); a/d < 2.5$ $V_c = 0.4 + 2.5 \times \sqrt{f_c \times \frac{\rho_w}{a/d}}; a/d \geq 2.5$	Eq. (15)
16	Bazant and Kim [49]	$V_c = \left(\frac{0.831\times\rho_w^{1/3}}{1+\frac{d}{25\times d_{max.}}}\right) \times \left(\sqrt{f_c} + 249 \times \sqrt{\frac{\rho_w}{a/d^5}}\right); d_{max.} = 19.1\ mm$ [31]	Eq. (16)
17	Bazant and Sun [48]	$V_c = 0.54 \times \rho_w^{1/3} \times \left(\frac{1+\sqrt{\frac{5.08}{d_{max.}}}}{\sqrt{1+\frac{d}{25\times d_{max.}}}}\right) \times \left(\sqrt{f_c} + \left(249.2 \times \sqrt{\frac{\rho_w}{a/d^5}}\right)\right)$	Eq. (17)
18	Pradhan et al. [51]	$V_c = 1.6 \times \frac{1}{RCA^{0.1}} \times fc^{0.6} \times \left(\frac{d_{max.}}{d}\right)^{0.48} \times \frac{1}{a/d^{0.91}}$	Eq. (18)

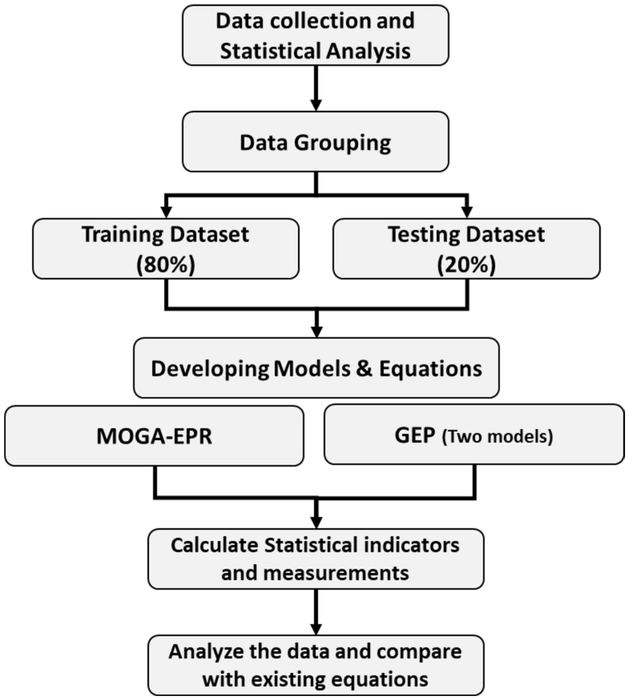

Fig. 1 Flowchart process for this paper methodology

ratio, compressive strength (fc), effective depth (d), beam width (b), shear span-to-effective depth ratio (a/d), and longitudinal reinforcement ratio (ρ_w). The observed shear force of concrete at the point of failure in all the specimens was referred to as $V_{c,\ experimental}$, while V_c was calculated in accordance with the equations in Table 1 and the model established in this study.

Table 2 shows the statistical measures for the collected experimental dataset provided by the reference [31].

3.2 Data grouping

This research assessed the capability of two Gene Expression Programming (GEP) models as well as a Multi-Objective Genetic Algorithm Evolutionary Polynomial Regression (MOGA-EPR) model and compared them to the equations listed in Table 1. To guarantee accuracy, the data was split into two parts: 80% for training the models and 20% for testing. The statistical values associated with the training and testing data sets respectively for both the GEP and MOGA-EPR models are shown in Tables 3 and 4.

Table 2 Statistical measures of the collected data

Statistical measure	RCA (%)	$f'c$ (MPa)	b (mm)	d (mm)	a/d	ρ_w (%)	$V_{experimental}$ (kN)
Min.	5.00	20.00	150.00	160.00	1.00	0.53	12.10
Max.	100.00	46.80	400.00	600.00	5.69	4.09	261.50
Average	68.48	32.54	206.52	310.85	3.02	1.67	82.40
STDEV	30.19	6.32	59.95	98.83	0.82	0.77	49.88

Table 3 Statistical measures of the training dataset

Statistical measure	RCA (%)	$f'c$ (MPa)	b (mm)	d (mm)	a/d	ρ_w (%)	$V_{experimental}$ (kN)
Min.	5.00	20.00	150.00	160.00	1.00	0.53	12.10
Max.	100.00	46.80	305.00	600.00	5.69	4.09	186.70
Average	69.49	32.54	203.18	301.25	3.06	1.70	80.22
STDEV	30.29	6.44	53.73	94.24	0.86	0.76	44.59

Table 4 Statistical measures of the testing dataset

Statistical measure	RCA (%)	$f'c$ (MPa)	b (mm)	d (mm)	a/d	ρ_w (%)	$V_{experimental}$ (kN)
Min.	10.00	21.50	150.00	160.00	1.50	0.59	12.10
Max.	100.00	46.50	400.00	600.00	4.40	3.02	261.50
Average	64.32	32.26	220.24	350.40	2.87	1.55	91.40
STDEV	30.02	5.89	80.66	109.12	0.65	0.82	67.90

Table 5 The main setting parameters and adjustments of GEP models

GEP parameter	Setting of parameters	
	Model (1)	Model (2)
Number of chromosomes	30	30
Head size	8	8
Number of genes	3	4
Function set	+, −, ×, /	+, −, ×, / and $\sqrt{}$
Fitness function	RMSE	RMSE
Mutation rate	0.00138	0.00138
Inversion rate	0.00546	0.00546
Gene transposition rate	0.00277	0.00277
Random chromosomes	0.0026	0.0026
Gene recombination rate	0.00277	0.00277

3.3 Developing the models

In this paper, a study is conducted to assess the effectiveness of two methods, GEP and MOGA-EPR, in predicting the shear force (strength) of 128 RC beams without stirrups from the literature. The accuracy of these models is largely due to their ability to account for the percentage of RAC, as only two of the literature (the modified ACI 318-19 (Eq. 4) and Pradhan et al. [51] (Eq. 18) sources examined in the study took this factor into account when formulating the equation for predicting shear force (strength) of concrete without stirrups.

3.3.1 Gene expression programming (GEP)

This research looked into GEP analysis using the GeneXproTools software [63]. Chromosomes are the primary building blocks of this process; they are linear, condensed, small in nature, and can be changed through genetic methods, like replication, mutation, recombination, and transposition. In addition, the chromosomes were then converted into tree expressions; this is where the selection process begins. After evaluation of the fitness levels, the chromosomes were chosen to be reproduced and altered. The chromosomes, not the tree expressions, are modified and then passed on to the next generation during reproduction [64].

Table 6 GEP model equations

Model #	Predicted shear force of concrete ($V_{c,p}$) Equation	Coefficients	Equation #
Model (1)	$V_{c,p} = \frac{(a_1 \times b)+b^2-(a_2 \times d)}{a_3+2b+\mathrm{RCA}} + \left(2\rho_w - f_c - \left(a_4 \times {}^{a}/_{d}\right) + 2a_5\right) \times a_6 + \frac{(\rho_w \times b)+RCA+d}{\left(a_7 - {}^{a}/_{d}\right) \times {}^{a}/_{d}} - a_7$	$a_1 = -21.0666762746255$ $a_2 = 7.11114125670014$ $a_3 = 70.0885238993207$ $a_4 = -6.46450922950747$ $a_5 = 11.7577632723312$ $a_6 = -1.86695567939283$ $a_7 = 8.22854901779607$	Equation (19)
Model (2)	$V_{c,p} = \frac{{{}^{a}/_{d}}^2 - (f_c \times \rho_w) + (b \times \rho_w)}{\sqrt{b_1 \times b_2}} + \frac{(f_c \times b_3) - (f_c \times \rho_w)}{{{}^{a}/_{d}}^2 - \rho_w} + f_c + \left(\left(b_4 - b_5\right) \times {}^{a}/_{d}\right) - \frac{b}{b_6} b_7 + \frac{(b_8 - d) \times \rho_w + RCA + b_8}{\frac{RCA}{b} + \rho_w - f_c}$	$b_1 = 9.48014095514551$ $b_2 = 9.8165906080672$ $b_3 = 2.76180982707257$ $b_4 = -5.4917681938966$ $b_5 = 6.97911007553723$ $b_6 = -2.95452232950374$ $b_7 = -4.20961242301417$ $b_8 = 373.456479221179$	Equation (20)

Table 7 MOGA- EPR model equation

Predicted Shear Force of concrete ($V_{c,p}$) Equation	Coefficients	Equation #
$V_{c,p} = c_1 \times \sqrt{b} \times RCA^2 + c_2 \times \sqrt{f_c} \times \sqrt{b} \times \sqrt{d} \times {{}^{a}/_{d}}^2 \times \rho_w + c_3 \times \sqrt{f_c} \times b^2 + c_4 \times \sqrt{f_c} \times b^2 \times \sqrt{{}^{a}/_{d}}$	$c_1 = -5.4202 \times 10^{-1}$ $c_2 = 2.8308 \times 10^{-3}$ $c_3 = 1.7978 \times 10^{-3}$ $c_4 = -9.479 \times 10^{-4}$	Equation (21)

Copying genetic material is not the only element of reproduction; genetic operators are needed to generate genetic diversity. Without these operators, simply replicating the genome would not create new genetic variants. The operators act randomly to decide which chromosomes will be altered and which will remain the same.

In this paper, as shown in Table 5, two various GEP models are formulated. The first one utilized the base operations (+, -, ×, and /) and the other included the square root function.

In Table 6, Eqs. 19 and 20 are developed taking into consideration all of the input variables that affect the shear force (strength) of concrete without stirrups.

3.3.2 Multi-objective evolutionary polynomial regression (MOGA- EPR)

MOGA-EPR (Multi-objective evolutionary polynomial regression analysis) is an effective computational tool that applies a genetic algorithm (GA) to determine the correlation between physical input variables via regression analysis. This method is advantageous over traditional regression techniques, as it eliminates the risk of overfitting and automatically finds the most suitable correlation through a search algorithm. To utilize the MOGA-EPR, the user must specify the correlation structure, the range of exponents, and the number of terms. For further details about the MOGA-EPR, see references [65–72].

Table 7 showcases the MOGA-EPR model equation which is used to estimate the shear strength of concrete without stirrups, taking into account all the relevant input variables. This equation is represented by Eq. (21).

3.4 Statistical indicators and measurements

A thorough examination of both new and existing analytical methods is conducted using statistical parameters such as mean absolute error (MAE), root mean squared error (RMSE), mean (μ), and coefficient of determination (R^2) (Eqs. 22–25). This is a common accuracy assessment approach that has been used in prior studies [73–77]. The MAE and RMSE values represent the perfect fit, with lower values signifying better performance. An ideal μ value should be 1.0; values greater than that suggest an overestimate of the shear strength ($V_{c,p}$) of concrete without stirrups, whereas smaller values signify an underestimate.

$$\mathrm{MAE} = \frac{1}{n}\sum_{1}^{n}\left|V_{c,p} - V_{c,m}\right| \tag{22}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(V_{c,p} - V_{c,m}\right)^2} \tag{23}$$

$$\mathrm{Mean}\,(\mu) = \frac{1}{n}\sum_{1}^{n}\left(\frac{V_{c,p}}{V_{c,m}}\right) \tag{24}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}(V_{c,p} - V_{c,p_{average}})(V_{c,m} - V_{c,m_{average}})}{\sqrt{\sum_{i=1}^{n}(V_{c,p} - V_{c,p_{average}})^2 \sum_{i=1}^{n}(V_{c,m} - V_{c,m_{average}})^2}}\right)^2 \tag{25}$$

In Eqs. 22–25, the number of data points (n) utilized for the evaluation is denoted, with $V_{c,p}$ depicting the predicted shear force of concrete and $V_{c,m}$ signifying the measured (experimentally) shear force of concrete.

4 Results

Table 8 shows the results of the mean absolute error (MAE), root mean squared error (RMSE), mean (μ) and coefficient of determination (R^2) of the GEP and MOGA-EPR approaches,

Table 9 Statistical accuracy comparison of the developed models using all of the datasets

Model	MAE (kN)	RMSE (kN)	Mean	STDV	R^2
GEP model (1)	12.74	17.61	1.02	0.34	0.88
GEP model (2)	11.43	15.44	1.04	0.23	0.90
MOGA-EPR	11.16	16.52	1.02	1.15	0.90

Table 8 Statistical measures of the testing and training datasets

Statistical measure	GEP Model (1)		GEP Model (2)		MOGA-EPR Model	
	Training data	Testing data	Training data	Training data	Training data	Testing data
MAE (MPa)	12.64	13.14	11.10	12.81	9.85	16.57
RMSE (MPa)	17.61	17.60	15.29	16.05	13.36	25.72
Mean (μ)	1.01	1.06	1.03	1.09	1.01	1.05
R^2	0.84	0.93	0.88	0.95	0.91	0.94

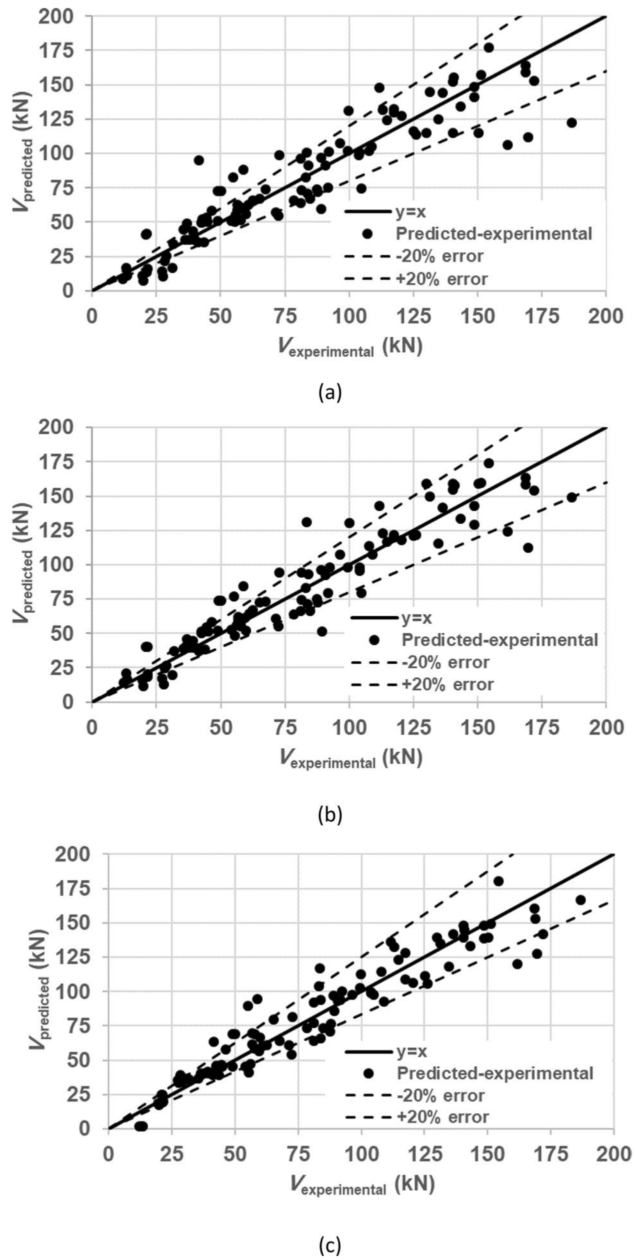

Fig. 2 Relationship between experimental and predicted shear force of concrete (V_c) using the developed models for the training dataset: **a** GEP model (1), **b** GEP model (2) and **c** MOGA-EPR

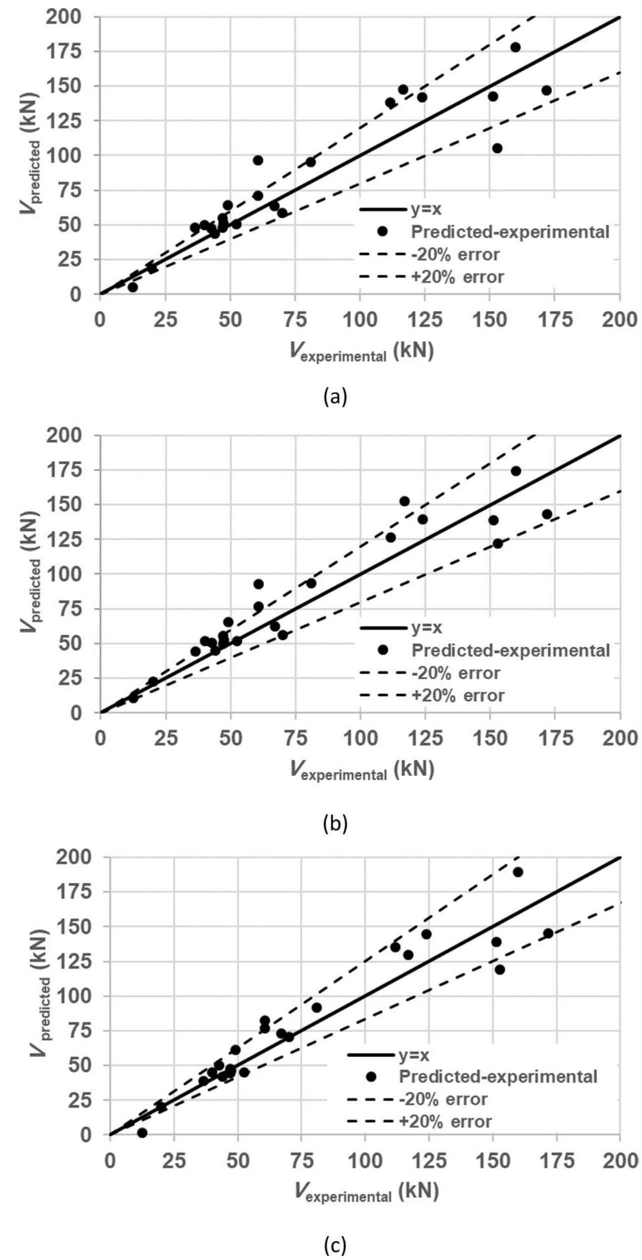

Fig. 3 Relationship between experimental and predicted shear force of concrete (V_c) using the developed models for the testing dataset: **a** GEP model (1), **b** GEP model (2) and **c** MOGA-EPR

which are calculated using the statistical indicators and measurements in Sect. 3.2. These results compare the predictions of the shear force of concrete (V_c) without stirrups by the training and testing datasets to the shear in concrete measured experimentally.

Table 8's results show that the MAE of the developed approaches is between 9.85 and 12.64 for the training datasets, and 12.81 and 16.57 for the test datasets. RMSE values for the training datasets range from 13.36 to 17.61, and 16.05 to 25.72 for testing datasets. The mean of the datasets is 1.01 to 1.03 for the training datasets and 1.05 to 1.09 for the testing datasets. Lastly, the R^2 scores for the training datasets range from 0.84 to 0.91 and 0.93 to 0.95 for the test datasets. The results from Table 8 are quite positive, with the MOGA-EPR model having the greatest R^2 value out of the three models for the training dataset, and the GEP model (2) having the highest R^2 for the testing dataset. All the models have mean values close to 1, suggesting that the models are performing well.

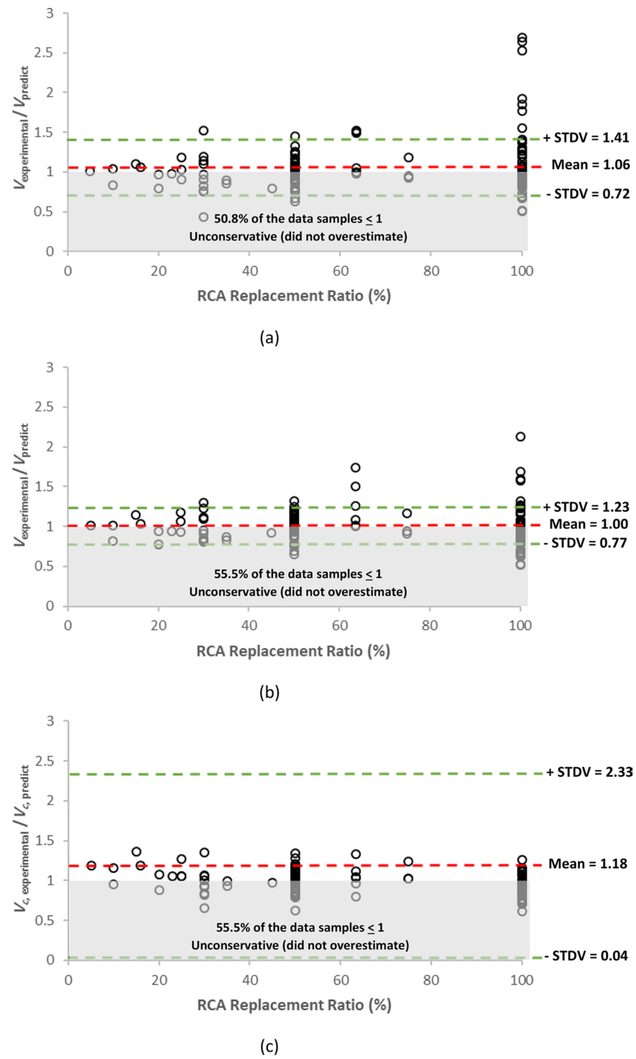

Fig. 4 Relationship between experimental and predicted Shear force of concrete ratio and the % of RCA replacement using the developed models for all of the datasets: **a** GEP model (1), **b** GEP model (2) and **c** MOGA-EPR

Table 9 presents the statistical metrics of all datasets for both the GEP and MOGA-EPR models. It can be seen that the R^2 scores of the GEP model (2) and MOGA-EPR are the same, at 0.90, and the score of the GEP model (1) is slightly lower but still relatively close. All models have mean values that are very close to 1, demonstrating their good performance.

Figures 2 and 3 compare the predicted and measured results from the training and testing datasets for the three models. Most of the predictions are close to the ideal fit line and fall within the ±20% error range, indicating accurate predictions.

The graph in Fig. 4 displays the comparison between the experimental shear force of concrete ($V_{c,\ experimental}$) and the predicted shear force of concrete ($V_{c,\ predicted}$) obtained by GEP and MOGA-EPR Eqs. (19–21). The mean ± standard deviation (STDV), for the ratios, is indicated in the graph. It is obvious that the majority of the shear force of concrete ratios are situated inside the range of the mean and standard deviation. The predicted shear force of concrete equations did not overestimate the force for any of the RCA replacement levels, as the experimental shear force of concrete was less than the predicted shear force of concrete ($V_{c,\ experimental}/V_{c,\ predicted} \leq 1$). Also, from Fig. 4, it can be seen that 50.8% of the data samples predicted by the GEP model (1) and 55.5% of the data samples predicted by the GEP model (2) and MOGA-EPR models had a shear force ratio that was lower than 1, indicating that the equations used to predict the shear force of concrete did not overestimate the force for any of the RCA replacements.

Table 10 Statistical accuracy comparison

Model/Reference	R^2	MAE (kN)	RMSE (kN)
GEP Model (2)	0.90	11.43	15.44
MOGA-EPR	0.90	11.16	16.52
GEP Model (1)	0.88	12.74	17.61
Gastebled and May [43]	0.84	17.72	26.19
Pradhan et al. [51]	0.84	17.36	21.74
Arslan [47]	0.83	15.79	22.43
Zsutty [40, 41]	0.82	18.77	29.24
Kim and Park [53]	0.81	16.48	24.36
CEB-FIP [39]	0.79	67.30	79.04
Bazant and Yu [37, 38]	0.77	33.12	43.79
ACI 318-19 [34]	0.76	23.49	34.15
Bazant and Sun [48]	0.76	21.05	31.61
Eurocode 2 [35]	0.75	64.69	76.36
ACI 318-19 Modified [31]	0.74	32.92	43.10
Rebeiz [45]	0.74	29.23	45.24
Bazant and Kim [49]	0.73	18.15	27.80
ACI 318-14 [33]	0.72	21.03	31.57
Rahal and Alrefaei [52]	0.72	30.95	41.67
Indian Standard:456 [36]	0.71	74.28	86.71
New Zealand code [46]	0.69	31.53	51.89
Niwa et al. [42]	0.60	20.72	33.77

5 Comparison with current codes and developed equations

This paper used GEP and MOGA-EPR methods to predict the shear force of concrete (V_c) beams without stirrups with RCA. 18 analytical equations were also evaluated for comparison. Table 9; Fig. 5 display the R^2, MAE, and RMSE for each of the models and references from the highest R^2 to the lowest.

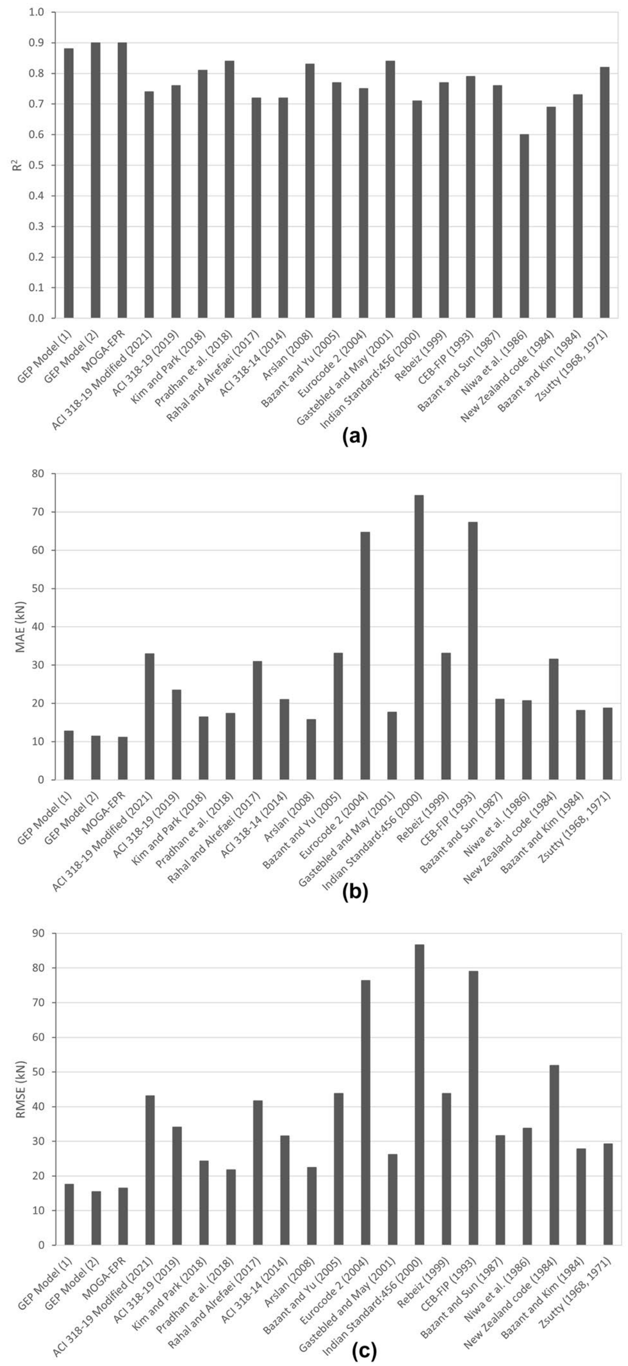

Fig. 5 Statistical accuracy comparison for the different models and equations for predicting the shear force of concrete (V_c): **a** R^2 , **b** MAE (kN) and **c** MSE (kN)

The results from Table 10; Fig. 5 indicate that the R^2 values range from 0.6 to 0.9, the MAE from 11.16 to 74.28 kN, and the RMSE from 15.44 to 86.71 kN. The developed prediction models by GEP and MOGA-EPR demonstrate the most accurate and precise performance in comparison to the experimental values, as indicated by the highest R^2 values of 0.9. Furthermore, GEP (2) and MOGA-EPR have the lowest MAE and RMSE in comparison with the other available analytical equations. It should be noted that the GEP and MOGA-EPR models, along with the Pradhan et al. [51] and the ACI 318−19 modified equation [31], are the only approaches that take into account the RCA ratio in their equation variables.

In addition to the values of R^2 mentioned in Table 10; Figs. 5 and 6 goes further by comparing the 18 analytical equations in the literature to these models, showing the cumulative frequency of the error level in percentage. It is clear from this figure that the MOGA-EPR and GEP models are on par with each other and better at predicting V_c than the other references.

Table 11 The average of experimental and predicted Shear force of concrete ratio for all of the models and equations

Model/Reference	Average of ($V_{experimantal}/V_{predict}$)	
CEB-FIP [39]	5.5	Conservative > 1.0 (Overestimating)
New Zealand code [46]	4.7	
Indian Standard:456 [36]	4.4	
ACI 318 – 19 Modified [31]	1.7	
Bazant and Yu [37, 38]	1.6	
Rahal and Alrefaei [52]	1.6	
ACI 318 – 19 [34]	1.4	
Bazant and Sun [48]	1.3	
ACI 318 – 14 [33]	1.3	
Niwa et al. [42]	1.3	
Bazant and Kim [49]	1.2	
Gastebled and May [43]	1.1	
Arslan [47]	1.1	
GEP Model (1)	1.0	
MOGA-EPR	1.0	
GEP Model (2)	1.0	
Eurocode 2 [35]	0.96	
Kim and Park [53]	0.95	
Zsutty [40, 41]	0.93	
Pradhan et al. [51]	0.88	
Rebeiz [45]	0.86	

Table 11; Fig. 7 show the average of the experimental to predicted shear force of concrete ratio for all of the models and equations from the highest to the lowest values. If the ratio is more than 1.0, then the model or equation is deemed conservative and overestimated [31]. The GEP and MOGA-EPR models were found to be accurate and precise, as the predicted values were not overestimated

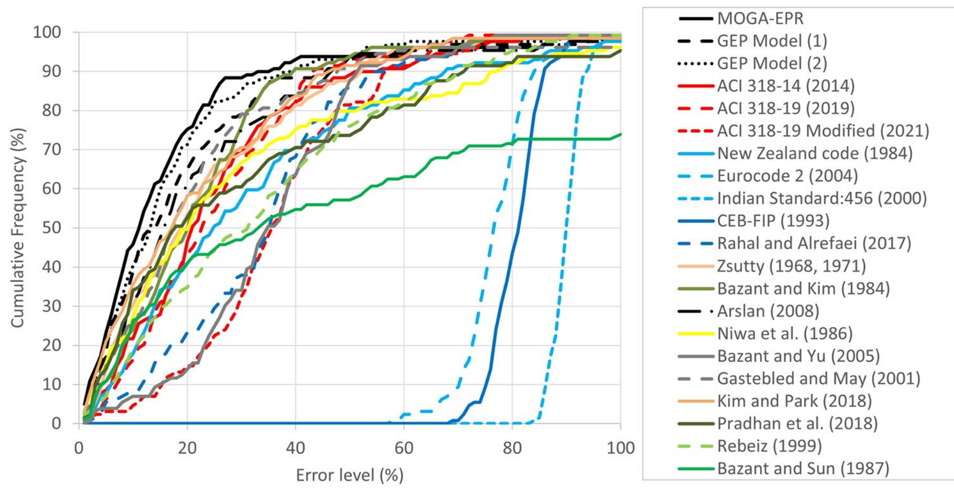

Fig. 6 Comparison of the error level for different cumulative frequencies

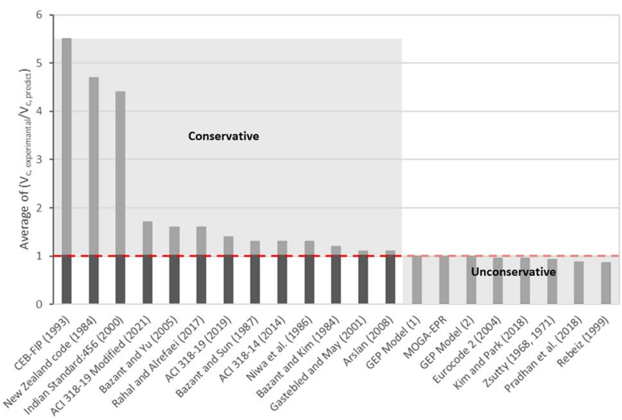

Fig. 7 The average of experimental and predicted Shear force of concrete ratio for all of the models and equations

and were close to the experimentally determined values. The same conclusion can be drawn from Table 12; Fig. 8. This table and figure present the percentage of the samples of experimental and predicted shear force of concrete ratio greater than 1.0 for all of the models and equations. This is useful to determine the conservative nature of the equations from the literature and the models developed by the GEP and MOGA-EPR. If the percentage of the # of predicted (or/and) calculated values by any of the models and equations (from 1 to 18) is greater than 50%, then the model or equation is considered to be conservative and overestimating the value of the predicted shear force of concrete.

Table 12 The percentage of the # of samples of experimental and predicted Shear force of concrete ratio > 1.0 for all of the models and equations

Model/Reference	% of Samples for ($V_{experimantal}/V_{predict}$) > 1.0	
CEB-FIP [39]	100.0	Conservative (Overestimating)
New Zealand code [46]	100.0	
Indian Standard:456 [36]	100.0	
ACI 318-19 Modified [31]	100.0	
ACI 318-19 [34]	91.4	
Bazant and Yu [37, 38]	90.6	
Rahal and Alrefaei [52]	89.1	
Bazant and Sun [48]	88.3	
ACI 318-14 [33]	73.4	
Bazant and Kim [49]	70.3	
Gastebled and May [43]	61.7	
Arslan [47]	60.9	
Niwa et al. [42]	57.0	
GEP Model (1)	49.2	
MOGA-EPR	44.5	
GEP Model (2)	44.5	
Eurocode 2 [35]	33.6	
Kim and Park [53]	39.8	
Zsutty [40, 41]	33.6	
Pradhan et al. [51]	28.1	
Rebeiz [45]	22.7	

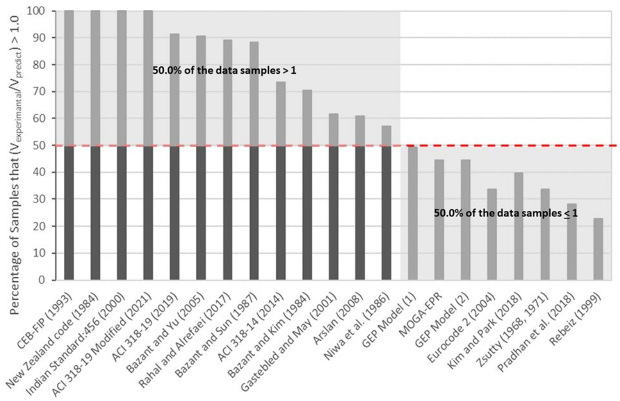

Fig. 8 The percentage of the # of samples of experimental and predicted Shear force of concrete ratio > 1.0 for all of the models and equations

6 Conclusions

The findings of this study indicated that MOGA-EPR and GEP are effective for predicting the shear strength of concrete beams with recycled aggregate, without the presence of stirrups. Three new models were created, giving designers an uncomplicated and powerful tool to use. The new methods were more precise and showed enhanced precision in comparison to the equations already existing in codes and literature.

The results of this study demonstrate the following conclusions with taking into consideration the constraints of the study:

(1) The three proposed models have higher accuracy than existing equations in the literature, with R^2 values of up to 0.90.
(2) The predicted results by using GEP and MOGA-EPR showed very good accuracy within the $\pm 20\%$ error range.
(3) GEP models 1 and 2 showed good accuracy with MAE of 11.43 kN and 12.74 kN, RMSE of 15.44 kN and 17.61 kN, Mean of 1.02 and 1.04, and R^2 of 0.88 and 0.90 respectively.
(4) The MOGA-EPR model demonstrated high accuracy with MAE of 11.16 kN, RMSE of 16.52, Mean of 1.02, and R^2 of 0.90.
(5) The models proposed by this study provide precise solutions and avoid overestimating shear strength (force) in concrete, contrary to existing equations from the literature.
(6) The three models consider all input variables, including recycled coarse aggregate replacement ratio, which other existing equations do not take into account.

This investigation brings to light the proposed system's potential future influence. This system joins a recognized soft computing technique with an artificial intelligence protocol to generate three practicable models. These models have the capabilities to be adopted on a broad scale and impact a number of industries, as they present a consistent and successful way of handling intricate matters that involve all the variables that other existing approaches do not take into account in their equations. The execution of these models could bring about significant progress in multiple areas and ultimately result in considerable advantages for practitioners and scholars. Future research should concentrate on validating and calibrating the proposed models using a variety of experimental data, extending their application to other structural elements, incorporating additional parameters, integrating them into design codes, and investigating the long-term durability of concrete with recycled aggregates and other aspects of concrete design. These efforts will improve the models' dependability, broaden their field of application, and encourage practical adoption and integration of AI, ultimately leading to more sustainable and efficient construction processes. Furthermore, enhancing accuracy demands the testing and validation of more mix design samples through increased experimental data.

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Author contributions A.A. and R.A. have written the paper and preparted the data S.A. have prepared EPR model A.A prepared GEP model.

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Data availability All data available in the study.

Declarations

Conflict of interest The authors declare no competing interests.

Ethical approval The authors state that the research was conducted according to ethical standards

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