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ORIGINAL ARTICLE

Evaluation of mechanical properties of concretes containing coarse recycled concrete aggregates using multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression (LSSVR) models

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Abstract

This paper investigates the application of three artificial intelligence methods, including multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression (LSSVR) for the prediction of the mechanical behavior of recycled aggregate concrete (RAC). A large and reliable experimental test database containing the results of 650 compressive strength, 421 elastic modulus, 152 flexural strength, and 346 splitting tensile strength tests of RACs with no pozzolanic admixtures assembled from the published literature was used to train, test, and validate the three data-driven-based models. The results of the model assessment show that the LSSVR model provides improved accuracy over the existing models in the prediction of the compressive strength of RACs. The results also indicate that, although all three models provide higher accuracy than the existing models in the prediction of the splitting tensile strength of RACs, only the performance of the LSSVR model exceeds those of the best-performing existing models for the flexural strength of RACs. The results of this study indicate that MARS, M5Tree, and LSSVR models can provide close predictions of the mechanical properties of RACs by accurately capturing the influences of the key parameters. This points to the possibility of the application of these three models in the pre-design and modeling of structures manufactured with RACs.

Keywords Recycled aggregate concrete (RAC) · Mechanical properties · Least squares support vector regression (LSSVR) · M5 model tree (M5Tree) · Multivariate adaptive regression splines (MARS)

1 Introduction

The high demand for concrete because of the rapid growth in urbanization and industrialization has resulted in an increase in the consumption of natural aggregates, which typically makes up approximately 70% of the total volume of concrete [1]. Furthermore, rapid industrialization and urbanization have led to an increase in the generation of construction and demolition (C&D) wastes, which consequently resulted in the depletion of landfill space [2, 3]. Over the past two decades, recycled aggregate concrete (RAC), obtained by crushing concrete sourced from C&D waste, has been considered as an alternative concrete material to conserve natural aggregate resources and to minimize the environmental impact of C&D waste [4, 5]. During this period, a large number of studies have been conducted to understand the mechanical behavior of RACs

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(e.g., [6–9]). Existing studies confirmed that compressive strength, elastic modulus, flexural strength, and splitting tensile strength are the main mechanical properties for design and analysis of RACs [10–12]. In addition, a comprehensive literature review [1] revealed that a number of models have been proposed either based on experimental test results of the original study [13, 37–48, 65–69] or compiled databases from the results of previous studies [14–18] to predict the mechanical properties of RACs. However, owing to the limitations in the number of input parameters considered, as well as the use of relatively small number of test results in the calibration of most existing models, these models are not generalizable. Therefore, additional studies are needed to investigate the mechanical properties of RACs using computationally economical techniques based on a comprehensive test database containing key input parameters.

Machine learning-based models have been extensively used to predict the properties of concrete [19–22]. Recently, with the development of computer-aided modeling methods, the use of artificial intelligence techniques has been considered to predict the mechanical behavior of RACs. Younis and Pilakoutas [23] used multilinear and nonlinear regression methods to develop a model for the prediction of the compressive strength of RAC. Duan et al. [24] and Sahoo et al. [25] predicted the compressive strength of RAC using artificial neural network (ANN) technique. Deshpande et al. [26] used ANN, M5Tree, and nonlinear regression methods for the prediction of the compressive strength of RAC. Duan et al. [27] and Behnood et al. [28] used ANN and M5Tree techniques for the prediction of the elastic modulus of RAC, respectively. Gonzalez-Taboada et al. [29] applied genetic programming and multivariable regression methods for the prediction of the compressive strength, elastic modulus, and splitting tensile strength of RAC. Recently, Ozbakkaloglu et al. [2] and Gholampour et al. [30] predicted the compressive strength, elastic modulus, flexural strength, and splitting tensile strength of RACs with the use of nonlinear regression and gene expression programming methods, respectively. However, most of these techniques were either computationally complex, unable to handle a large number of databases, or unable to accurately capture the influences of the key input parameters for solving nonlinear problems. Therefore, more robust and simple artificial intelligence techniques should be applied to predict the properties of RACs.

In recent years, data-driven techniques, such as multivariate adaptive regression splines (MARS), M5 model tree (M5Tree), and least squares support vector regression (LSSVR) models, have received a significant attention to solve critical civil engineering problems. MARS is a nonlinear and nonparametric regression method, and its main advantages are efficiency and robustness to explore a large number of intricate nonlinear relations and rapid detection of interactions between them despite their complexity [31]. M5Tree model is a binary decision tree with a series of linear regression functions, and its main advantages are the simple geometric structure and the ability to efficiently handle a large number of datasets with different attributes [32]. LSSVR is a statistical learning model, which adopts a least squares linear system as a loss function instead of the quadratic program in the original support vector machine (SVM) [33]. LSSVR solves a set of linear equations by linear programming that is computationally very simple [33]. Recent studies illustrated that because of their main advantages of (1) easy handling of a large number of databases, (2) computational simplicity, and (3) strong ability of solving nonlinear problems, MARS, M5Tree, and LSSVR models can be efficient alternatives to existing artificial intelligence methods in solving key civil engineering problems. Cheng and Cao [34] used MARS model to predict the shear strength of reinforced concrete beams. Behnood et al. [28] applied M5Tree model for the prediction of the elastic modulus of RACs. Aiyer et al. [35] applied LSSVR model to predict the compressive strength of self-compacting concrete. Pham et al. [36] predicted the compressive strength of high-performance concretes using LSSVR model. However, no study has been reported to date on the application of LSSVR and MARS models for the prediction of the mechanical properties of RAC and only a single study on the application of M5Tree model for the prediction of the elastic modulus of RAC.

To address the above-mentioned research gaps, three robust artificial intelligence techniques, namely MARS, M5Tree, and LSSVR, were adopted in this study for the prediction of the compressive strength, elastic modulus, flexural strength, and splitting tensile strength of RAC. Existing experimental test database of RACs is initially presented, which is followed by the details of the three models developed in this study. Subsequently, an assessment of the prediction results of the three models is presented.

2 Experimental test database

The database of RAC, presented in Gholampour et al. [30], was assembled based on 69 experimental studies published in the open literature on RACs containing no pozzolanic admixtures. The RAC database consisted of 332, 318, 421, 152, and 346 datasets, respectively, for compressive strength of cube specimens ($f_{\mathrm{cm,cube}}$), compressive strength of cylinder specimens ($f_{\mathrm{cm,cylinder}}$), elastic modulus (E_c), flexural strength (f_r), and splitting tensile strength (f_{st}).

The cylinder specimens had either a 100 or 150 mm diameter and a 200 or 300 mm height; the cube specimens had a dimension of either 100 or 150 mm; and beams had a dimension of either 100 × 100 × 500 mm or 150 × 150 × 750 mm. Effective water-to-cement ratio (w_{eff}/c) of specimens varied from 0.19 to 0.87, coarse recycled concrete aggregate replacement ratio (RCA%) varied from 0 to 100, aggregate-to-cement ratio (a/c) varied from 1.2 to 6.5, bulk density of recycled concrete aggregate (ρ_{RCA}) varied from 1946 to 2720 kg/m^3, water absorption of coarse recycled concrete aggregate (WA_{RCA}) varied from 1.5 to 11.9%. In addition, $f_{cm,cube}$, $f_{cm,cylinder}$, E_c, f_r, and f_{st} in the database ranged from 18.9 to 104.3 MPa, 26.6 to 61.2 MPa, 12.5 to 50.4 GPa, 1.9 to 10.2 MPa, and 1.1 to 6.3 MPa, respectively. The distribution of the histogram of the key parameters (i.e., w_{eff}/c, RCA%, a/c, ρ_{RCA}, and WA_{RCA}) for the specimens in the database is illustrated in Fig. 1.

3 Existing models for the prediction of mechanical properties of RAC

Models proposed to date for the prediction of the mechanical properties of RACs were assembled from 21 different studies, as previously presented in Gholampour et al. [30]. All models contained closed-form expressions obtained from regression analysis of the test results. Furthermore, two sets of expressions recently proposed by Gholampour et al. [30] through the use of gene expression programming (GEP) and Ozbakkaloglu et al. [2] using regression analysis were also considered in the present study. Existing models include 11 models for compressive strength [2, 15, 16, 23, 30, 37–39], 18 models for elastic modulus [2, 13–15, 30, 40–47, 65, 66], six models for flexural strength [2, 15, 30, 45–47], and eight models for splitting tensile strength [2, 15, 16, 30, 43, 46–48] of RAC.

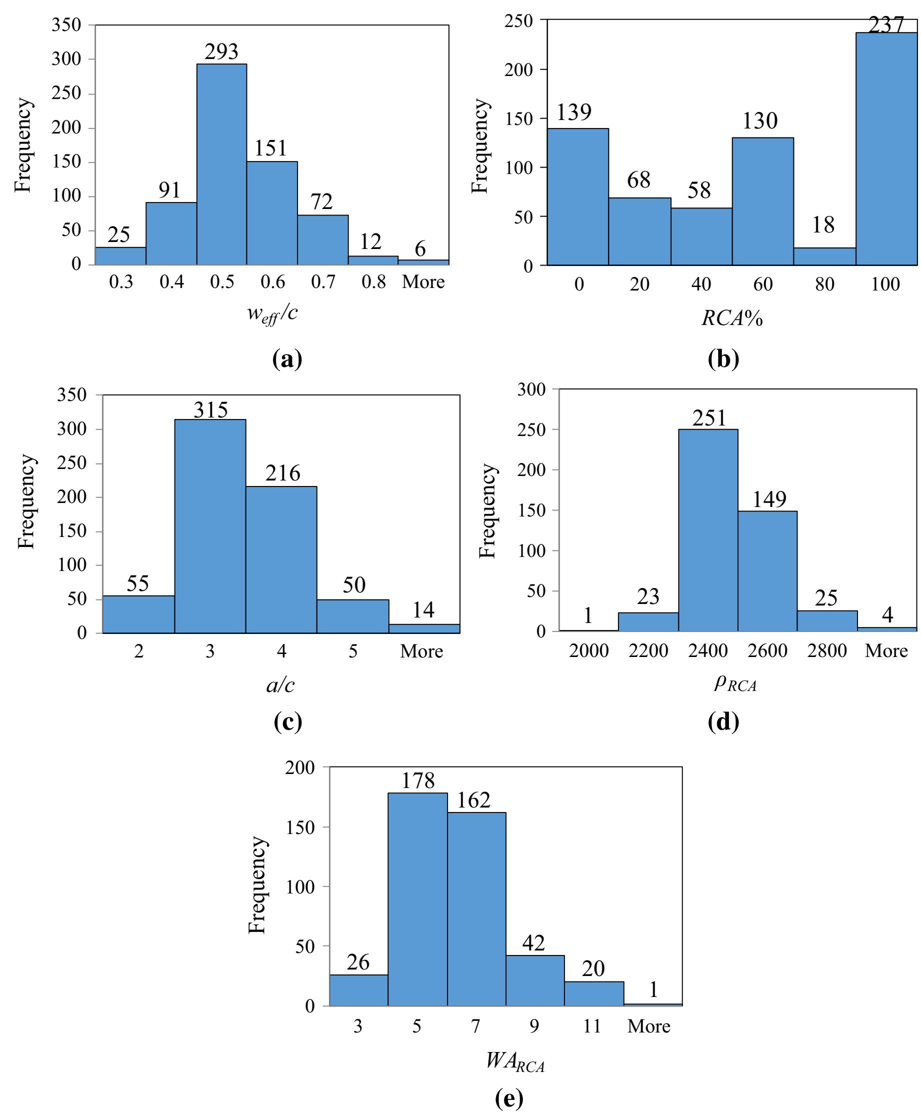

Fig. 1 Histogram distribution of: **a** w_{eff}/c, **b** RCA%, **c** a/c, **d** ρ_{RCA}, and **e** WA_{RCA}

4 Overview of MARS, M5Tree, and LSSVR models

4.1 Multivariate adaptive regression splines (MARS)

MARS is a form of regression analysis that was developed by Friedman [31] for the prediction of continuous numerical outcomes. Its algorithm consists of a forward and backward stepwise procedure [49]. The backward procedure removes the unnecessary variables among the previous selected set in the forward procedure to improve the prediction accuracy. Therefore, the variable X is transferred to variable Y using either of the following equations by an inflection point along the input values [50]:

$$Y = \max(0, X - c) \quad \text{or} \quad \max(0, c - X) \tag{1}$$

in which c is a threshold value. In MARS, a function applies for each input variable in forward–backward stepwise procedure to find the location of the inflection point in which the function value changes. MARS is a nonparametric statistical technique in which piecewise curves and polynomials give flexible results that can handle not only linear but also nonlinear behavior [49]. Detailed information about MARS is available in Ref. [50].

4.2 M5 model tree (M5Tree)

M5Tree model, which was originally proposed by Quinlan [32], is based on a binary decision tree with a series of linear regression functions at the terminal (leaf) nodes. In the first stage, a decision tree is created by splitting the data into subsets and assuming the standard deviation of class values that reach a node as a measure of the error at that node. Subsequently, the expected reduction in the error as a result of testing each attribute at the node is calculated. The standard deviation reduction (SDR), which is used to describe the reduction in the error, is defined as follows [51]:

$$\mathrm{SDR} = \mathrm{sd}(T) - \sum \frac{|T_i|}{T} \mathrm{sd}(T_i) \tag{2}$$

where T, T_i, and sd represent a set of examples that reach the node, subset of examples that have the ith outcome of the potential set, and standard deviation, respectively. Because of the splitting process, the standard deviation of data in child nodes (i.e., lower nodes) becomes lower than that of parent node. The split that maximizes the expected error reduction is selected after examining all possible splits [32].

4.3 Least squares support vector regression (LSSVR)

LSSVR, proposed by Suykens and Vandewalle [33], is a supervised learning method based on the principle of structural risk minimization. By considering a given training set of $\{x_k, y_k\}_{k=1}^{N}$ with input data of $x_k \in R^n$ and output data of $y_k \in R$ with class labels of $y_k \in \{-1, +1\}$, the linear classifier in the primal space is defined as:

$$y(x) = \mathrm{sign}\left(w^T \varphi(x) + b\right) \tag{3}$$

in which b is a real constant. LSSVR is defined in dual space for nonlinear classification as:

$$y(x) = \mathrm{sign}\left(\sum_{k=1}^{N} \alpha_k y_k K\left(x_k^T, x\right) + b\right) \tag{4}$$

in which α_k is a positive real constant and $K\left(x_k^T, x\right)$ is a kernel function that is defined as $\varphi(x_k), \varphi(x)$, where $\varphi(x)$ is a nonlinear map from original space to the high-dimensional space. The following expression is used to estimate a function:

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x_k, x) + b \tag{5}$$

In order to use radial basis function (RBF) kernel in the modeling, two tuning parameters of γ and σ are added to Eq. 5, in which γ and σ are regularization constant and width of RBF kernel, respectively. The main advantage of LSSVR compared to support vector regression (SVR) is the use of the linear squares principle for the loss function in the LSSVR. In the SVR, however, quadratic programming is employed for this purpose, which is not computationally efficient. Consequently, LSSVR is faster than the SVR in computation [52]. Detailed information about LSSVR can be obtained from Ref. [53].

5 Prediction of mechanical properties of RAC

MARS, M5Tree, and LSSVR techniques were applied to estimate the compressive strength, elastic modulus, flexural strength, and splitting tensile strength of RAC. The main parameters influencing the mechanical properties of RACs were determined based on the accurate assessment of the specimens in the database. Based on this assessment, it was found that w_{eff}/c, RCA%, a/c, ρ_{RCA}, and $\mathrm{WA}_{\mathrm{RCA}}$ are the most influential parameters on the mechanical behavior of RACs. Therefore, these parameters were used as inputs to the models. The number of data points available for the validation and testing of the models was 171, 156, 224, 79,

Table 1 Model predictions of cube compressive strength ($f_{cm,cube}$) of RAC

Model	Number of all datasets	RMSE (MPa)	MAE (MPa)	MAPE (%)	Specimen type
Xiao et al. [15]	74	11.3	4.7	12.7	Cube
Pereira et al. [38]	157	11.8	9.4	22.2	Cube
Gholampour et al. [30]	156	8.9	5.5	12.7	Cube
MARS	156	9.1	5.4	13.0	Cube
M5Tree	156	8.3	5.9	14.2	Cube
LSSVR	156	7.7	4.6	12.6	Cube

and 168 for $f_{cm,cylinder}$, $f_{cm,cube}$, E_c, f_r, and f_{st} of RACs, respectively. For each model, 80% of the database was used for training and validation of the models and remaining 20% was used for testing. The results of the three models were subsequently compared with the existing models using the root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) (also referred to as the average absolute error, AAE, in previous studies) statistics to evaluate the performance of the three models. Definitions of these statistical indicators are given as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{Mod}_i - \mathrm{Exp}_i)^2} \tag{6}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\mathrm{Mod}_i - \mathrm{Exp}_i| \tag{7}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{Mod}_i - \mathrm{Exp}_i| \times 100}{\mathrm{Exp}_i} \tag{8}$$

where Mod_i and Exp_i are the estimated and experimental values of mechanical properties of RAC and n is the number of time steps.

An open-source code (http://www.esat.kuleuven.be/sista/lssvmlab/) was used for the LSSVR model. Various numbers from 1 to 100 were tried for γ and σ control parameters. The optimal γ and σ values were calculated as 15.6 and 3.0 for $f_{cm,cube}$, 17.1 and 3.3 for $f_{cm,cylinder}$, 22.4 and 4.4 for E_c, 7.9 and 1.5 for f_r, and 16.8 and 3.3 for f_{st} of RAC, respectively. For MARS and M5Tree techniques, open-source codes (http://www.cs.rtu.lv/jekabsons/regression.html) were used.

5.1 Compressive strength

In order to assess the accuracy of the compressive strength models, their performance was evaluated using the test database. Based on the available input parameters in the test database, only six compressive strength models [2, 15, 30, 38, 39] could be used in the model assessments, among which three of them were for cube specimens and three for cylinder specimens. The remaining models [16, 23, 37] required specific inputs that were not available in the database.

Table 1 shows the prediction statistics of MARS, M5Tree, and LSSVR models and existing models for $f_{cm,cube}$ of RAC. It can be seen in the table that the model by Gholampour et al. [30] was the best-performing $f_{cm,cube}$ model in the literature. However, LSSVR model provided improved accuracy over the existing models in predicting $f_{cm,cube}$. This observation can be attributed to the ability of the model to accurately capture the influences of the key input parameters (i.e., w_{eff}/c, RCA%, a/c, ρ_{RCA}, and WA_{RCA}) in the analysis. Figure 2 shows the comparison of MARS, M5Tree, and LSSVR model predictions with the experimental $f_{cm,cube}$ at the validation stage. As can be seen in the figure, LSSVR model developed a higher accuracy in predicting $f_{cm,cube}$ of RACs than that of MARS and M5Tree models.

Table 2 shows the prediction statistics of MARS, M5Tree, and LSSVR models and existing models for $f_{cm,cylinder}$ of RAC. As can be seen in the table, those by Gholampour et al. [30] showed the best performance among the existing models. It can be seen in Table 2 that only LSSVR model performed better than the existing models in predicting $f_{cm,cylinder}$. Figure 3 shows the comparison of MARS, M5Tree, and LSSVR model predictions with the experimental $f_{cm,cylinder}$ at the validation stage. As can be seen in the figure, similar to the case of $f_{cm,cube}$, LSSVR model exhibited a higher accuracy in the prediction of $f_{cm,cylinder}$ of RACs compared to that of MARS and M5Tree models. This is attributed to the fact that LSSVR is based on a learning method that is dependent on the statistical learning theory. In this method, the use of a regularization parameter helps to avoid over-fitting in the modeling [54].

5.2 Elastic modulus

Table 3 illustrates the prediction statistics of MARS, M5Tree, and LSSVR models and existing models for E_c of RACs. As can be seen in the table, Ozbakkaloglu et al. [2],

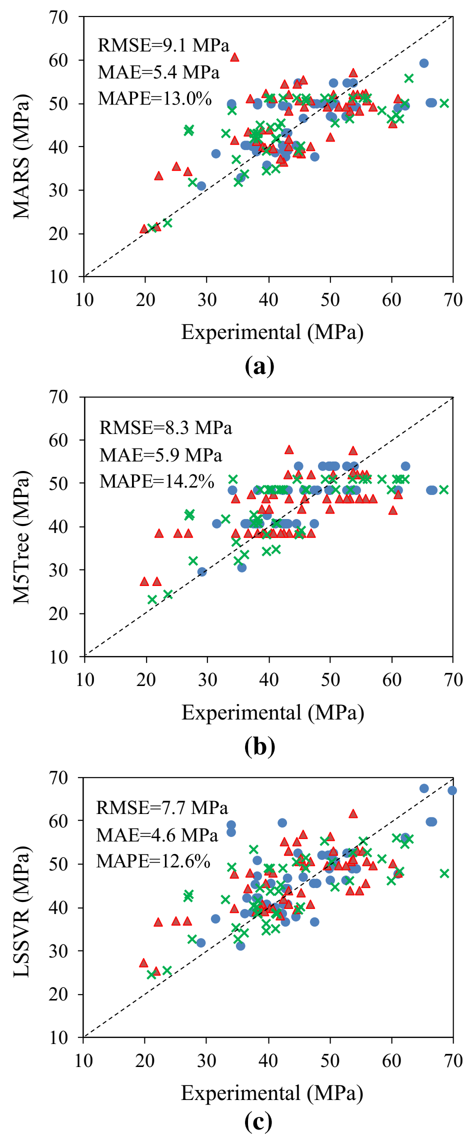

Fig. 2 Compressive strength estimates of cube RAC ($f_{cm,cube}$) by **a** MARS, **b** M5Tree, **c** LSSVR models at the validation stage. Circle-, triangle-, and cross-shaped points are data points for validation set 1, 2, and 3, respectively

Rahal [40], Corinaldesi [41], and Zilch and Roos [14] models showed the best performance among the models in the literature to predict E_c of RAC. As can also be seen in Table 3, MARS, M5Tree, and LSSVR models provide nearly identical accuracy to that of the best-performing models in the literature in the prediction of E_c of RACs. Furthermore, MARS, M5Tree, and LSSVR models provided improved accuracy over Gholampour et al. [30] model in the prediction of E_c of RACs.

Figure 4 shows the comparison of MARS, M5Tree, and LSSVR model predictions with the experimental E_c of RACs at the validation stage. As can be seen in the figure, LSSVR model developed a higher accuracy in predicting the E_c of RAC than that of M5Tree and MARS models, confirming the suitability of the LSSVR model for this application.

5.3 Flexural strength

Table 4 illustrates the prediction statistics of MARS, M5Tree, and LSSVR models and existing models for f_r of RACs. As can be seen in the table, the models by Ozbakkaloglu et al. [2], Xiao et al. [15], and Gholampour et al. [30] performed the best for the prediction of f_r of RAC among the existing models. It can be seen in Table 4 that LSSVR model provided slightly higher accuracy than those of the best-performing models in the literature in the prediction of f_r of RACs. Comparison of MARS, M5Tree, and LSSVR model predictions with the experimental results shown in Fig. 5 further illustrates the better accuracy of the LSSVR model compared to that of MARS and M5Tree models in the prediction of the f_r of RACs.

5.4 Splitting tensile strength

Table 5 illustrates the comparison of prediction statistics of MARS, M5Tree, and LSSVR models with those of existing models in predicting the f_{st} of RAC. As can be seen in the table, Ozbakkaloglu et al. [2], Tavakoli and Soroushian [46], Xiao et al. [15], and Gholampour et al. [30] models performed the best among the existing models. It can also be seen in Table 5 that MARS, M5Tree, and LSSVR models provided improved accuracy over these best-performing models in the prediction of f_{st} of RACs. The results

Table 2 Model predictions of cylinder compressive strength ($f_{cm,cylinder}$) of RAC

Model	Number of all datasets	RMSE (MPa)	MAE (MPa)	MAPE (%)	Specimen type
Ozbakkaloglu et al. [2]	257	8.0	4.7	14.5	Cylinder
Thomas et al. [39]	257	8.1	4.8	14.6	Cylinder
Gholampour et al. [30]	171	7.9	5.3	14.5	Cylinder
MARS	171	8.4	6.4	16.3	Cylinder
M5Tree	171	8.2	6.4	16.5	Cylinder
LSSVR	171	7.4	4.6	14.3	Cylinder

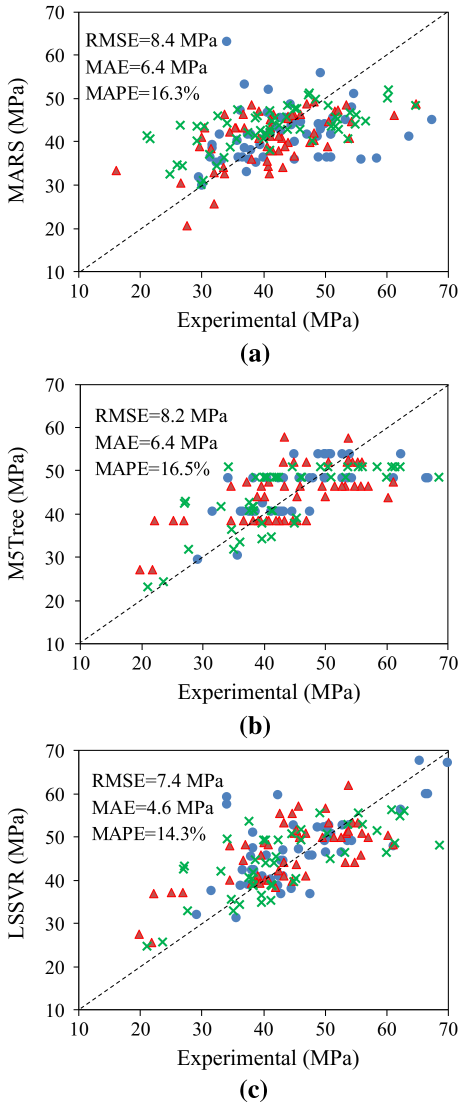

Fig. 3 Compressive strength estimates of cylinder RAC ($f_{\mathrm{cm,cylinder}}$) by **a** MARS, **b** M5Tree, **c** LSSVR models at the validation stage. Circle-, triangle-, and cross-shaped points are data points for validation set 1, 2, and 3, respectively

suggest that all the three models are suitable for the prediction of the splitting tensile strength of RACs, which varies with the considered input parameters in a highly nonlinear fashion. However, in some cases, data-driven models (e.g., MARS) may over-fit the data in training period and provide lower accuracy in test period compared to the simple models (e.g., regression method).

Figure 6 shows the comparison of MARS, M5Tree, and LSSVR model predictions with the experimental f_{st} results of RACs at the validation stage. It can be seen in the figure that LSSVR model provided higher accuracy than that of MARS and M5Tree models in estimating the f_{st} of RAC.

Table 3 Model predictions of elastic modulus (E_c) of RAC

Model	Number of all datasets	RMSE (GPa)	MAE (GPa)	MAPE (%)
Ozbakkaloglu et al. [2]	351	3.09	2.23	10.8
Ravindrarajah and Tam [13]	104	5.62	4.21	13.1
Kakizaki et al. [65]	33	4.51	3.64	10.9
Bairagi et al. [45]	104	6.76	5.55	19.1
de Oliveira and Vazquez [66]	104	7.14	6.19	22.3
Tavakoli and Soroushian [46]	104	6.55	5.29	16.8
Dillmann [67]	104	8.40	6.57	21.7
Dhir [68]	104	5.15	4.29	14.3
Zilch and Roos [14]	84	3.10	2.23	8.3
Kheder and Al-Windawi [47]	172	6.76	8.12	18.7
Xiao et al. [15]	104	6.17	4.46	14.3
Rahal [40]	84	3.74	2.74	10.1
Corinaldesi [41]	172	3.85	3.13	10.1
Lovato et al. [16]	204	21.80	21.40	70.6
Hoffmann et al. [42]	172	7.65	6.85	21.5
Pereira et al. [43]	82	10.54	9.07	31.1
Wardeh et al. [44]	104	5.79	4.86	17.2
Gholampour et al. [30]	224	4.44	3.41	14.4
MARS	224	3.78	2.66	11.5
M5Tree	224	3.74	2.71	11.7
LSSVR	224	3.25	2.35	10.7

6 Variation of model predictions with influential parameters

In order to illustrate the variations of the model predictions with key input parameters within a physically meaningful framework, the variations of MARS, M5Tree, and LSSVR model predictions of $f_{\mathrm{cm,cube}}$, $f_{\mathrm{cm,cylinder}}$, E_c, f_r, and f_{st} with w_{eff}/c, RCA%, a/c, ρ_{RCA}, and $\mathrm{WA_{RCA}}$ are investigated. As was discussed in detail in Ref. [30], w_{eff}/c and RCA% have an accumulative effect on the mechanical properties of RACs. Therefore, the datasets used at the validation stage were divided into two subgroups based on their RCA% (i.e., RCA% of 0–50% and 51–100%) to better isolate the individual effects of w_{eff}/c and RCA% on the mechanical behavior of RACs.

Figures 7, 8, 9, 10, and 11 show the variation of model predictions of $f_{\mathrm{cm,cube}}$, $f_{\mathrm{cm,cylinder}}$, E_c, f_r, and f_{st} of RACs with w_{eff}/c at each RCA% interval, respectively. As can be seen in the figures and as expected, an increase in w_{eff}/c resulted in a decrease in each mechanical property of

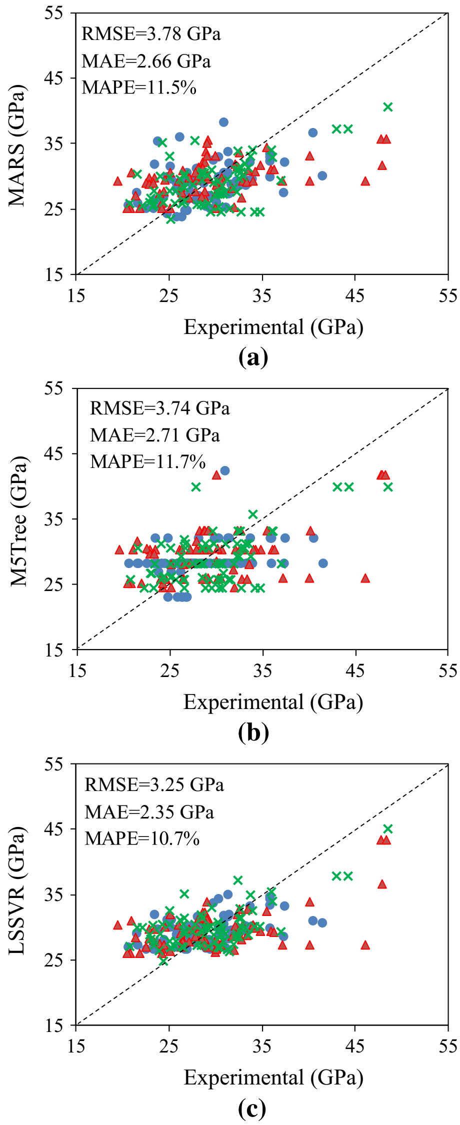

Fig. 4 Elastic modulus (E_c) estimates of RAC by **a** MARS, **b** M5Tree, **c** LSSVR models at the validation stage. Circle-, triangle-, and cross-shaped points are data points for validation set 1, 2, and 3, respectively

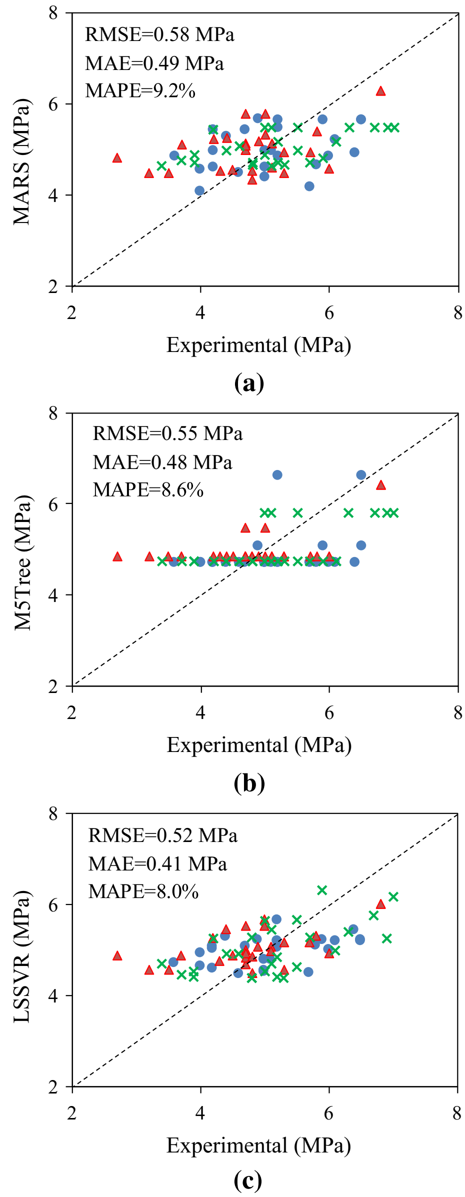

Fig. 5 Flexural strength (f_r) estimates of RAC by **a** MARS, **b** M5Tree, **c** LSSVR models at the validation stage. Circle-, triangle-, and cross-shaped points are data points for validation set 1, 2, and 3, respectively

Table 4 Model predictions of flexural strength (f_r) of RAC

Model	Number of all datasets	RMSE (MPa)	MAE (MPa)	MAPE (%)
Ozbakkaloglu et al. [2]	118	0.52	0.42	8.1
Bairagi et al. [45]	19	0.73	0.59	11.1
Tavakoli and Soroushian [46]	19	1.12	1.01	17.9
Kheder and Al-Windawi [47]	54	0.97	0.76	16.1
Xiao et al. [15]	19	0.52	0.45	8.1
Gholampour et al. [30]	79	0.54	0.45	8.3
MARS	79	0.58	0.49	9.2
M5Tree	79	0.55	0.48	8.6
LSSVR	79	0.52	0.41	8.0

Table 5 Model predictions of splitting tensile strength (f_{st}) of RAC

Model	Number of all datasets	RMSE (MPa)	MAE (MPa)	MAPE (%)
Ozbakkaloglu et al. [2]	307	0.51	0.48	15.9
Tavakoli and Soroushian [46]	109	0.57	0.44	20.3
Kheder and Al-Windawi [47]	139	0.77	0.65	23.1
Xiao et al. [48]	109	0.67	0.52	16.6
Xiao et al. [15]	109	0.52	0.46	16.6
Lovato et al. [16]	149	2.50	2.29	76.4
Pereira et al. [43]	58	0.78	0.57	17.3
Gholampour et al. [30]	168	0.64	0.50	16.5
MARS	168	0.60	0.47	15.8
M5Tree	168	0.61	0.47	15.7
LSSVR	168	0.53	0.46	15.6

RACs. It can also be seen in Figs. 7, 8, 9, 10 and 11 that these properties decreased with increasing RCA% at a given w_{eff}/c. It can be seen in the figures that all the three models are able to accurately capture the effects of w_{eff}/c and RCA% on the mechanical behavior of RACs to well reproduce the test results.

Figures 12, 13, 14, 15 and 16, respectively, illustrate the variation of $f_{cm,cube}$, $f_{cm,cylinder}$, E_c, f_r, and f_{st} of RACs with a/c, ρ_{RCA}, and WA_{RCA}. As can be seen in the figures, an increase in a/c and ρ_{RCA} resulted in an increase in each mechanical property of RACs, whereas an increase in WA_{RCA} led to a decrease in the mechanical properties of RACs. These observations are in agreement with the previous studies [41, 55–64]. Therefore, all the three models are capable of accurately predicting the trend of the variation of the mechanical behavior of RACs with key influential parameters.

7 Comparison of model predictions with design code expressions

In order to investigate the agreement of predictions of MARS, M5Tree, and LSSVR models of mechanical properties of conventional concrete (RCA%= 0) with those of existing design code and standard expressions, their overall trends were compared, as shown in Fig. 17. Table 6 shows the existing code expressions given for the prediction of E_c, f_r, and f_{st} of conventional concrete based on mean and characteristic cylinder compressive strength ($f_{cm,cylinder}$ and $f'_{c,cylinder}$). Figure 17 shows the variation of the predictions of E_c, f_r, and f_{st} by code expressions and

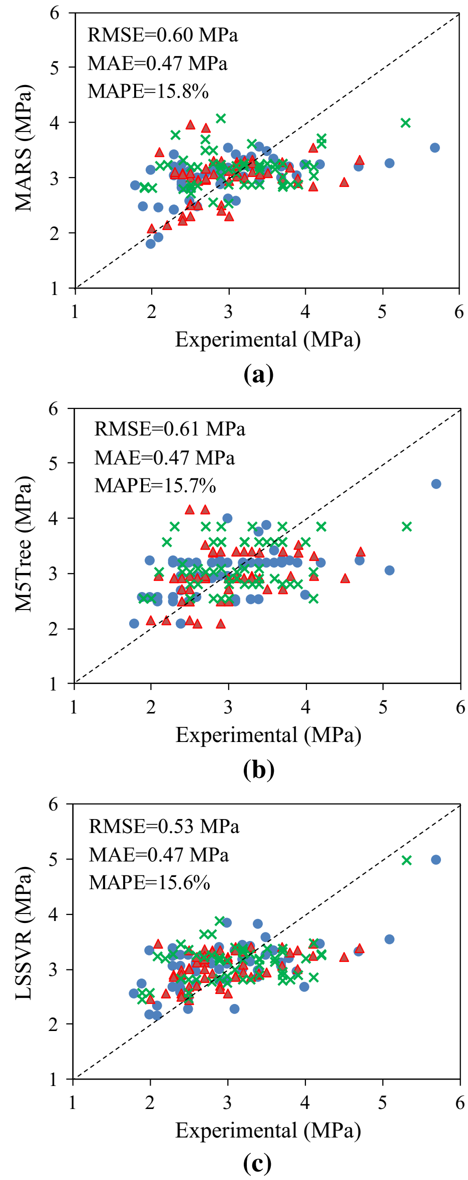

Fig. 6 Splitting tensile strength (f_{st}) estimates of RAC by **a** MARS, **b** M5Tree, **c** LSSVR models at the validation stage. Circle-, triangle-, and cross-shaped points are data points for validation set 1, 2, and 3, respectively

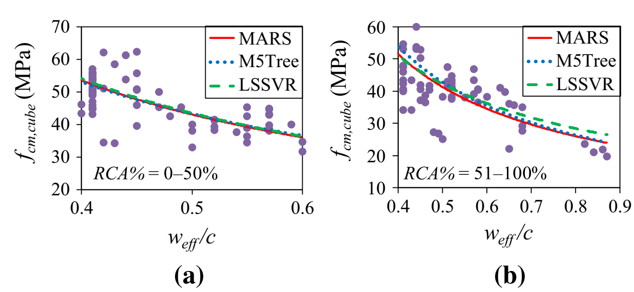

Fig. 7 Variation of model predictions of $f_{cm,cube}$ with w_{eff}/c: **a** RCA%= 0–50%, **b** RCA%= 51–100%. Data points show experimental test results at the validation stage

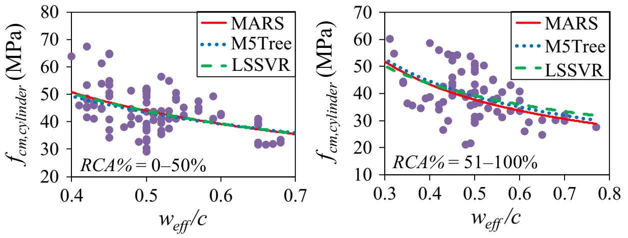

Fig. 8 Variation of model predictions of $f_{\mathrm{cm,cylinder}}$ with w_{eff}/c: **a** RCA%= 0–50%, **b** RCA%= 51–100%

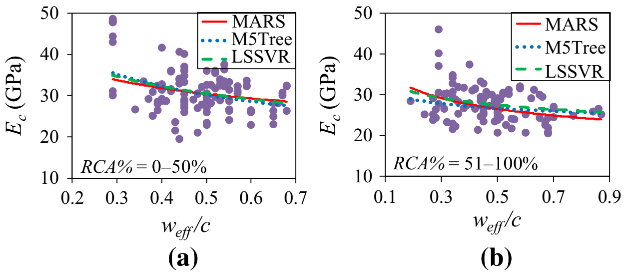

Fig. 9 Variation of model predictions of E_c with w_{eff}/c: (a) RCA%= 0–50%, (b) RCA%= 51–100%

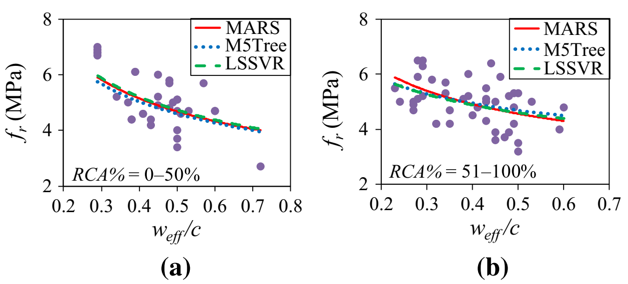

Fig. 10 Variation of model predictions of f_r with w_{eff}/c: **a** RCA%= 0–50%, **b** RCA%= 51–100%

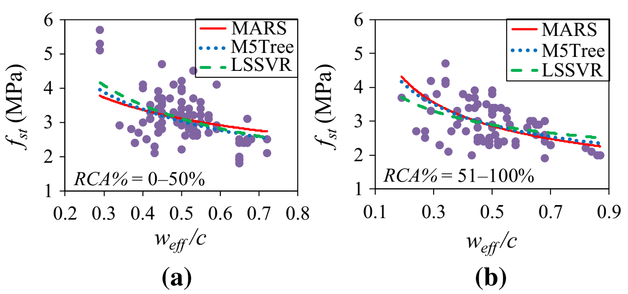

Fig. 11 Variation of model predictions of f_{st} with w_{eff}/c: **a** RCA%= 0–50%, **b** RCA%= 51–100%

MARS, M5Tree, and LSSVR models with $f'_{\mathrm{c,cylinder}}$. The comparison of the results shown in Fig. 17 indicates that the trends of the MARS, M5Tree, and LSSVR models are consistent with the overall trend of the existing code expressions for conventional concrete.

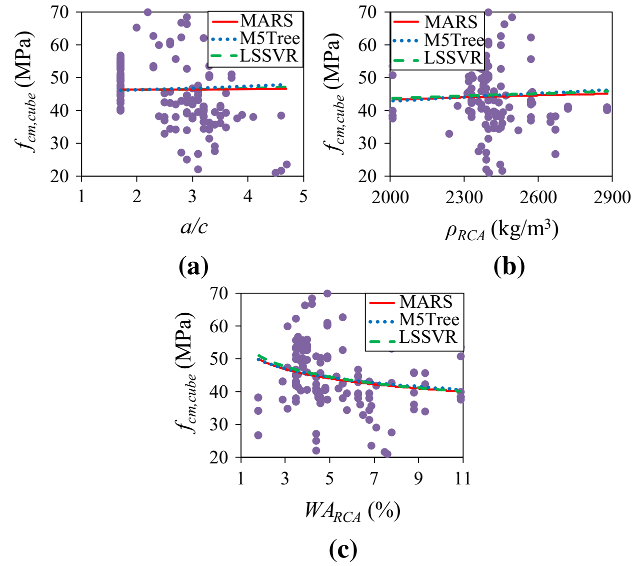

Fig. 12 Variation of model predictions of $f_{\mathrm{cm,cube}}$ with: **a** a/c, **b** ρ_{RCA}, and **c** $\mathrm{WA_{RCA}}$

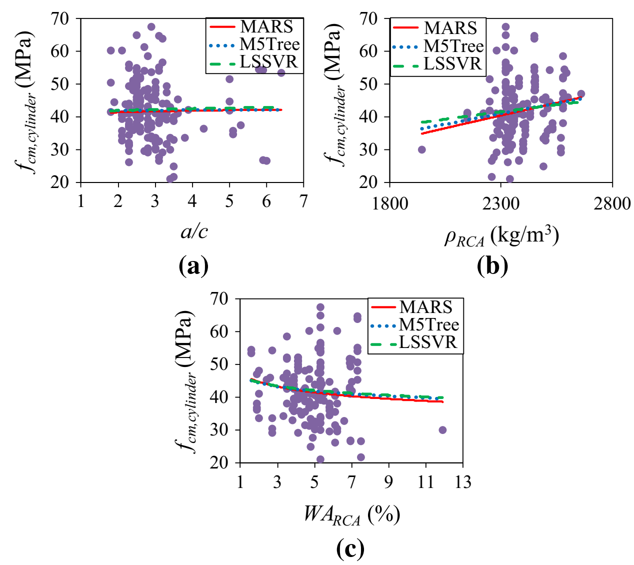

Fig. 13 Variation of model predictions of $f_{\mathrm{cm,cylinder}}$ with: **a** a/c, **b** ρ_{RCA}, and **c** $\mathrm{WA_{RCA}}$

8 Conclusions

This paper has presented an investigation into the capability of three artificial intelligence models, including MARS, M5Tree, and LSSVR, for the prediction of the

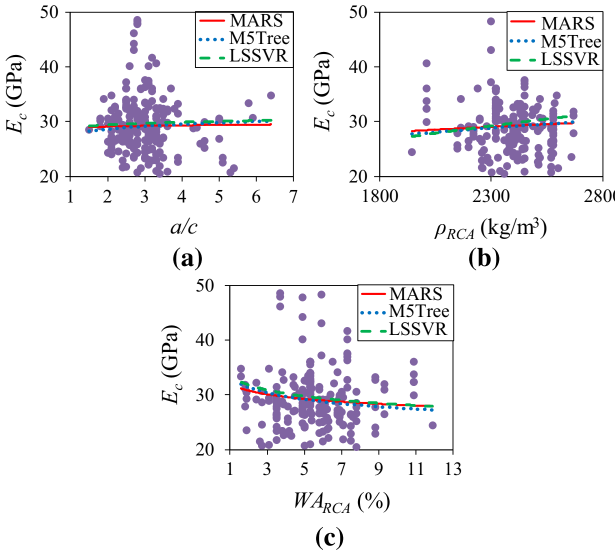

Fig. 14 Variation of model predictions of E_c with: **a** a/c, **b** ρ_{RCA}, and **c** $\mathrm{WA_{RCA}}$

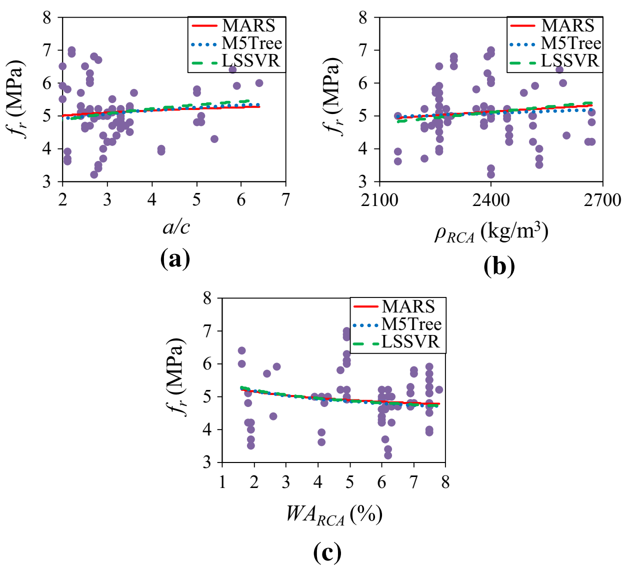

Fig. 15 Variation of model predictions of f_r with: **a** a/c, **b** ρ_{RCA}, and **c** $\mathrm{WA_{RCA}}$

compressive strength, elastic modulus, flexural strength, and splitting tensile strength of RACs. The test database of RAC was used to evaluate the performance of MARS, M5Tree, and LSSVR models and existing models in the literature. On the basis of assessment of modeling results, the following conclusions can be drawn:

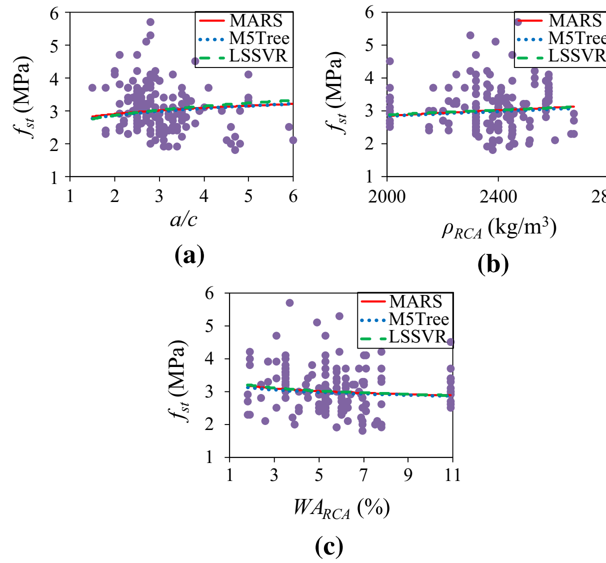

Fig. 16 Variation of model predictions of f_{st} with: **a** a/c, **b** ρ_{RCA}, and **c** $\mathrm{WA_{RCA}}$

1. LSSVR model provides a higher accuracy for the prediction of the compressive strength of cube and cylinder RACs (MAPE = 12.6 and 14.3%, respectively) compared to those of existing models.
2. The accuracy of MARS (MAPE = 11.5%), M5Tree (MAPE = 11.7%), and LSSVR (MAPE = 10.7%) models for predicting the elastic modulus of RAC is nearly identical to that of best-performing existing models.
3. MARS (MAPE = 9.2%) and M5Tree (MAPE = 8.6%) models predict the flexural strength of RACs with a slightly lower accuracy than that of the best-performing existing models, whereas LSSVR model (MAPE = 8.0%) performs better than the existing models.
4. All three models of MARS (MAPE = 15.8%), M5Tree (MAPE = 15.7%), and LSSVR (MAPE = 15.6%) perform better than the existing models in the prediction of the splitting tensile strength of RACs.
5. LSSVR model performs better than MARS and M5Tree models in predicting the compressive strength, elastic modulus, flexural strength, and splitting tensile strength of RACs.
6. For conventional concrete, the predictions of the MARS, M5Tree, and LSSVR models are in agreement with those of the existing concrete design code expressions.

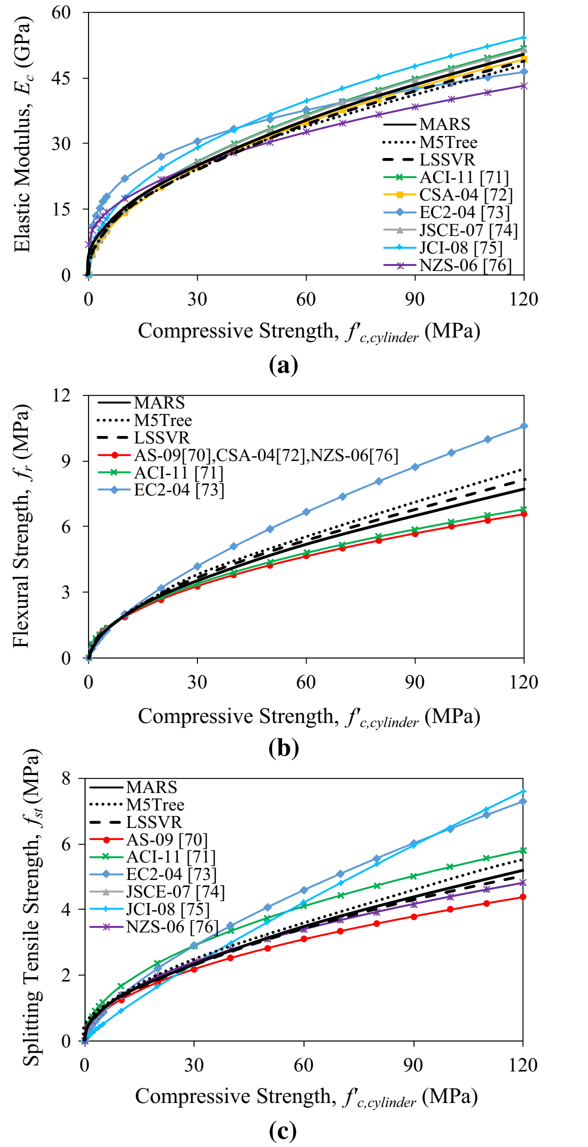

Fig. 17 Comparisons of models of the present study with models given in design codes for conventional concrete: **a** elastic modulus, **b** flexural strength, **c** splitting tensile strength

The results of this study indicate that MARS, M5Tree, and LSSVR models can provide close predictions of the mechanical properties of RACs by accurately capturing the influences of the key parameters, including the effective water-to-cement ratio, recycled concrete aggregate replacement ratio, aggregate-to-cement ratio, bulk density of recycled concrete aggregate, and water absorption of recycled concrete aggregate. These findings are promising and point to the possibility of the application of these techniques in the pre-design and modeling of structures manufactured with RACs.

Table 6 Summary of conventional concrete mechanical property models given in current design codes

Model	Elastic modulus (E_c) (GPa)	Flexural strength (f_r) (MPa)	Splitting tensile strength (f_{st}) (MPa)
AS 3600-09 [70]	$E_c = 4.3 \times 10^{-5} (\rho_h)^{1.5} \sqrt{f_{\mathrm{cm,cylinder}}}$ when $f_{\mathrm{cm,cylinder}} \leq 40\mathrm{MPa}$*	$f_r = 0.60\sqrt{f'_{\mathrm{c,cylinder}}}$	$f_{\mathrm{st}} = 0.4\sqrt{f'_{\mathrm{c,cylinder}}}$
	$E_c = \left(2.4(\rho_h)^{1.5}\sqrt{f_{\mathrm{cm,cylinder}}} + 12\right) \times 10^{-5}$ when $40 < f_{\mathrm{cm,cylinder}} \leq 100\,\mathrm{MPa}$		
ACI 318-11 [71]	$E_c = 4.73\sqrt{f'_{\mathrm{c,cylinder}}}$	$f_r = 0.62\sqrt{f'_{\mathrm{c,cylinder}}}$	$f_{\mathrm{st}} = 0.53\sqrt{f'_{\mathrm{c,cylinder}}}$
CSA A23.3-04 [72]	$E_c = 4.5\sqrt{f'_{\mathrm{c,cylinder}}}$	$f_r = 0.60\sqrt{f'_{\mathrm{c,cylinder}}}$	–
Eurocode 2-04 [73]	$E_c = 22(f_{\mathrm{cm,cylinder}}/10)^{0.3}$	$f_r = 0.435 f'^{\,2/3}_{\mathrm{c,cylinder}}$	$f_{\mathrm{st}} = 0.3\left(f'_{\mathrm{c,cylinder}}\right)^{2/3}$
JSCE-07 [74]	$E_c = 4.7\sqrt{f'_{\mathrm{c,cylinder}}}$	–	$f_{\mathrm{st}} = 0.44\sqrt{f'_{\mathrm{c,cylinder}}}$
JCI-08 [75]	$E_c = 6.3 f'^{\,0.45}_{\mathrm{c,cylinder}}$	–	$f_{st} = 0.13\left(f'_{\mathrm{c,cylinder}}\right)^{0.85}$
NZS 3101:2006 [76]	$E_c = 3.32\left(\sqrt{f'_{\mathrm{c,cylinder}}}\right) + 6.9$	$f_r = 0.60\sqrt{f'_{\mathrm{c,cylinder}}}$	$f_{\mathrm{st}} = 0.44\sqrt{f'_{\mathrm{c,cylinder}}}$

$f'_{\mathrm{c,cylinder}}$, $f_{\mathrm{cm,cylinder}}$, f_r, and f_{st} are in MPa, E_c is in GPa, and ρ_h is in kg/m^3

* $f_{\mathrm{cm,cylinder}}$ and $f'_{\mathrm{c,cylinder}}$ are the mean and characteristic cylinder compressive strength, respectively ($f'_{\mathrm{c,cylinder}} = f_{\mathrm{cm,cylinder}} - 8$ MPa as per Eurocode 2)

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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