Cleaner Materials 3 (2022) 100044

Contents lists available at ScienceDirect

Cleaner Materials

journal homepage: www.elsevier.com/locate/clema

Compressive strength of concrete with recycled aggregate; a machine learning-based evaluation

Hamed Dabiri [a,*], Mahdi Kioumarsi [b], Ali Kheyroddin [c], Amirreza Kandiri [d], Farid Sartipi [e]

[a] School of Science and Technology, University of Camerino, Camerino, Italy
[b] Department of Civil Engineering and Energy Technology, OsloMet–Oslo Metropolitan University, 0166 Oslo, Norway
[c] Faculty of Civil Engineering, Semnan University, Semnan, Iran
[d] School of Civil Engineering, University College Dublin, Belfield, Dublin 4, Ireland
[e] Institute of Construction Material, Sydney, NSW 2747, Australia

A R T I C L E I N F O

Keywords:
Recycled aggregate concrete
Compressive strength
Machine learning
ANN
Regression
Random forest

A B S T R A C T

In the recent decades, researchers have shown an increased interest in the reusing recycled concrete aggregate generated by buildings' demolitions because of the undeniable economic and environmental benefits. The main objective of this research is therefore to evaluate the influence of replacing natural fine and coarse aggregate on the 3-, 7- and 28-day compressive strength of concrete using machine learning-based approaches. To this aim, the paper is presented in two parts. Firstly, linear, nonlinear regression and Random Forest methods are used to propose prediction models for estimating compressive strength of concrete with recycled aggregate. Then, the results are compared to those of Artificial Neural Network and M5P models available in the literature in terms of performance metrics parameters and Taylor diagram. Consequently, the most accurate model is introduced and used in the second part for assessing the effect of using recycled aggregates on the concrete compressive strength. To this end, three 10-set databases are generated by replacing natural fine, coarse and both of them with recycled fine, coarse and both of them, respectively, by the portions of 0–90% with the step of 10%. The compressive strength predicted by the ML-based model are evaluated in three different testing ages (3, 7 and 28 days). The results proved the high accuracy of the proposed prediction models and Random Forest model which was developed in this study was the most accurate model. Moreover, it was concluded that incorporating recycled aggregate could decrease compressive strength insignificantly. Finally, reduction in long-term strength of the concrete containing recycled fine aggregate is less than those containing coarse aggregate or both fine and coarse aggregate.

1. Introduction

Concrete is undoubtedly one of the most widely used materials in construction because of its undeniable benefits in terms of strength, durability in corrosive environments, inexpensive cost, application, etc. On the other hand, since natural aggregate (NA) are one of the main components of concrete mixtures, concrete is claimed to raise significant environmental complications by (a) using natural resources of aggregate, (b) CO_2 emission, (c) deposition of concrete buildings' demolition and landfill saturation (Manzi et al., 2013; Yang et al., 2011; Kazmi et al., 2020). As a result, application of innovative materials (e.g., elastomeric material), supplementary cementitious materials (SCMs), alkali-activated materials (AAMs) or recycled materials (e.g., glass particles) as a replacement for natural aggregate has been assessed in several studies (Dabiri et al., 2018; Dabiri and Kheyroddin, 2017; Gravina et al., 2021; Kaish et al., 2021; Steyn et al., 2021; Xiao et al., 2020; Xiao et al., 2021; Rahla et al., 2019).

Among several proposed materials, recycled concrete aggregate generated from reinforced concrete (RC) buildings' demolition has attracted researchers' attention because of reusing wasted concrete aggregate released in the nature which leads to remarkable advantages including: (a) reducing CO_2 emission, (b) preserving natural resources, (c) reducing waste deposition, (d) decreasing areas required for landfill disposal and overall (e) eliminating harmful influences of wasted concrete on environment (Manzi et al., 2013; Yang et al., 2011; Kazmi et al., 2020; Matar and Barhoun, 2020; Vieira et al., 2020).

* Corresponding author.
E-mail address: hamed.dabiri@unicam.it (H. Dabiri).

https://doi.org/10.1016/j.clema.2022.100044
Received 18 October 2021; Revised 11 December 2021; Accepted 5 January 2022

Nomenclature

Abbreviations

AI	Artificial intelligent
ANN	Artificial neural network
ANNGA	ANN with Genetic Algorithm
ANNGOA	ANN with Grasshopper Optimization Algorithm
ANNSSA	ANN with Slap Swarm Algorithm
CA	Coarse aggregate
CNA	Concrete containing natural aggregate
CNN	Convolutional neural network
CR	Concrete containing recycled aggregate
CRA	Recycled coarse aggregate to total coarse aggregate
CS	Compressive strength
FA	Fine aggregate
FCA	Fine and coarse aggregate
FRA	Recycled fine aggregate to total fine aggregate
GBRT	Gradient boosting regression tree
LR	Linear regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
NA	Natural aggregate
NCA	Natural coarse aggregate
NFA	Natural fine aggregate
NFCA	Natural fine and coarse aggregate
NLR	Nonlinear regression
OPC	Ordinary Portland cement
PCC	Pearson correlation coefficient
R2	Coefficient of determination
RA	Recycled aggregate
RC	Reinforced concrete
RCA	Recycled coarse aggregate
RF	Random forest
RFA	Recycled fine aggregate
RFCA	Recycled fine and coarse aggregate
RMSE	Root mean square error
S	Sand
SP/C	Superplasticizer to cement ratio
std	Standard deviation
W/C	Water to cement ratio

1.1. Brief literature on the application of RCA

Several studies have been carried out to evaluate the effect of replacing natural aggregate (NA) with recycled aggregate (RA) on mechanical and physical properties of concrete (Tam et al., 2018; Bai et al., 2020; Thomas et al., 2020; Cantero et al., 2020; Mi et al., 2020). A major portion of research assessing compressive strength (CS) of concrete containing recycled aggregate (CR) has proved that compressive strength of CR is insignificantly lower than that of concrete with natural aggregate (CNA). It should be taken into account that the reduction in compressive strength is considerably affected by testing age (Matar and Barhoun, 2020; Bai et al., 2020; Xiao et al., 2005; Kou et al., 2012; Rahal, 2007). As an instance, the 28-day compressive strength of CR is reported approximately 90% lower than that of CNA (Matar and Barhoun, 2020; Rahal, 2007). Compressive strength of CR could be significantly enhanced by using waterproofing admixture (Matar and Barhoun, 2020). The effect of recycled aggregate size has been also studied by researchers. Abid et al. concluded that splitting tensile strength decreases by 35%, 33% and 39% while flexural strength reduces by 33%, 28% and 41% for the concrete containing fine, coarse and mixed recycled aggregate, respectively (Abid et al., 2018). Vo et al. have also confirmed the reduction in both workability and unit weight of concrete incorporating fine aggregate (Vo et al., 2021). Kang and Weibin claimed that compressive strength of concrete with recycled aggregate increases by increasing the size of recycled aggregate size because of the adhered old mortar: the smaller aggregate adhere to more old mortar which affect mechanical property of concrete negatively (Kang and Weibin, 2018). Aliabdo et al., however, concluded that the compressive strength reduction of concrete incorporating fine recycled aggregate is neglectable while in the case of replacing coarse aggregate with recycled aggregate, concrete strength decreases significantly (Aliabdo et al., 2014). Concrete with treated recycled aggregate has claimed to exhibit higher compressive strength than that with non-treated RA. Treatment could also reduce water absorption of CR by 7.27–12.17%. It is worth explaining that treatment is a process which aims at removing loose particles and old mortars attached to the concrete aggregates emerged from buildings demolition. Several techniques have been introduced by researchers for treating recycled aggregate namely microwave heating method, thermal or heating method, ultrasonic bath method, heating then rubbing method and acid method. In the last method, which is known as the simplest one, the recycled concrete aggregate is soaked in different acid types (hydrochloric acid, sulphuric acid, and phosphoric acid) for 24 h. Acid treatment could enhance compressive strength, flexural strength and elasticity modulus of concrete containing treated recycled aggregate compared to those with untreated recycled aggregate (Ismail and Ramli, 2013; Tam et al., 2007). The age of RA could also have a remarkable effect on compressive strength. It is claimed that the recycled aggregate utilized within 48 h after its production might lead to acceptable results due to reduction in the extra cement consumption (Vieira et al., 2020). The sample testing age could affect mechanical properties of concrete with RA remarkably. For instance, the 28-day tensile strength of a sample with RA is lower than that of CNA, while the 90-day tensile strength of CR is reported higher than that of CNA at 28 days (Kou et al., 2012).

The results of examinations of CR could be found in the literature and the interested readers are referred to (Tam et al., 2018; Bai et al., 2020; Kou et al., 2011; Evangelista and de Brito, 2007; Wang et al., 2021). Briefly noted: (a) the influence of incorporating recycled aggregate on ductility and pumpability could be notable, the reduced ductility due to incorporating recycled aggregate could be enhanced by using steel fibers and fiber reinforced polymer (FRP) (Chaboki et al., 2018; Gao et al., 2019) (b) the air content (porosity) in freshly mixed CR is higher than that of CNA (Matar and Barhoun, 2020; Vieira et al., 2020; Sadeghi-Nik et al., 2019), (c) elastic modulus and density of CR is lower than that of CNA while peak strain of CR is higher than that of CNA (Thomas et al., 2020; Xiao et al., 2005) and (d) water absorption of CR is higher than that of CNA because of higher porosity and lower density (Kazmi et al., 2020; Sadeghi-Nik et al., 2019).

1.2. The application of ML in assessing CS of CR

The application of machine learning- (ML) and regression-based methods in different fields of science has increased in the recent decades because of their simplicity and accuracy. In civil engineering, ML and regression models have been also attracted researchers' concern for proposing prediction models in different aspects such as structural performance, structural health monitoring and material properties (Salehi and Burgueño, 2018; Flah et al., 2021; Sun et al., 2021;

Ramkumar et al., 2020; Kioumarsi et al., 2020; Ahmadi et al., 2020; Bypour et al., 2021).

Several ML-based prediction models have been proposed by researchers in order to predict mechanical and physical properties of concrete with recycled aggregate (Chaabene et al., 2020). The proposed methods are confirmed to be a reliable alternative approach for costly and time-consuming experimental tests conducted in order to determine concrete properties.

Deng et al. (Deng et al., 2018) proposed a convolutional neural network (CNN) model for predicting strength of CR considering input variables including water-cement ratio, recycled coarse aggregate (RCA) ratio, recycled fine aggregate (RFA) ratio and their combination. Several artificial neural network (ANN) prediction models have been developed and discussed by Duan et al. (Duan et al., 2021) for obtaining CS of CR. It was revealed that ICA-XGBoost model might result in more accurate values in comparison to other ANN methods including ICA-ANN, ICA-SVR and ICA-ANFIS. An ensemble ML model was proposed by Han et al. (Han et al., 2020) to predict elastic modulus of CR. Performance metrics of the proposed models was compared to those of other ML models (e.g., linear regression, gaussian process regression, support vector machine, Random Forest and multilayer perceptron ANN) and it was concluded that the accuracy of the ensemble ML models was remarkably higher than other approaches. A gradient boosting regression tree (GBRT) model was introduced by Nunez and Nehdi (Nunez and Nehdi, 2021) to predict carbonation depth of CR incorporating different mineral additions. Xu et al. (Xu et al., 2019) applied a mathematical approach called gray system theory in order to evaluate parametric sensitivity for mechanical properties of CR. Furthermore, multiple linear regression- and ANN-based approaches were used to predict mechanical properties of CR mixes identified by the gray system theory. The optimal CR mixture was designed by Zhang et al. (Zhang et al., 2020) using a hybrid intelligent system based on artificial intelligence (AI) and metaheuristic algorithm. In the research, a multi objective optimization model based on AI algorithm and a multi-objective firefly algorithm were used to obtain the optimal CR mixture and it was figured out that Random Forest (RF) and Backpropagation neural network might lead to the most accurate outcomes.

2. Research significance, novelty and methodology

As mentioned in the previous section, the application of recycled aggregate as a replacement for natural aggregate could be environmentally and economically beneficial. Meanwhile, it should be taken into consideration that the compressive strength of concrete with recycled aggregate is slightly lower than that of concrete with natural aggregate. Strength of concrete incorporating recycled aggregate, however, could be enhanced by considering some simple solutions offered in the literature such as replacing the optimal percentage of natural aggregate by recycled aggregate. Finding the most effective RA replacement (fine aggregate, FA; coarse aggregate, CA; or both, FCA) by experimental tests is clearly costly and time-consuming. On the other hand, high-accurate ML-based methods are proved as a reliable alternative simple and quick approach to this aim. To the best knowledge of the authors, however, no previous research has assessed compressive strength of concrete containing different portions of recycled fine aggregate (RFA), recycled coarse aggregate (RCA) or both (RFCA) in different testing ages using AI.

In the present study, therefore, RF, linear regression (LR) and nonlinear regression (NLR) models are proposed for predicting compressive strength of concrete containing recycled aggregate. The accuracy of the models proposed in this study and those proposed in the previous study (Kandiri et al., 2021) is compared and discussed using common performance metrics and Taylor diagram. The most reliable and appropriate model is introduced and used for the second part of the study. In order to investigate the influence of incorporating recycled aggregate on concrete strength, a concrete mixture is selected from the peer-reviewed international publication (Poon et al., 2004) and the natural aggregate (FA, CA and FCA) are replaced with recycled aggregate (RFA, RCA and RFCA) by the step of 10% (0, 10%, 20%, …, 90%). The predicted compressive strength of concrete with recycled aggregate in different testing ages (3, 7 and 28 days) is assessed and eventually the optimal percentage of NA to be replaced with RA is presented. Briefly noted, the accuracy of different ML- and regression-based methods are compared together in the first part, while the influence of recycled aggregate on concrete compressive strength is evaluated in the second part. It is also worth noting in that the previous study (Kandiri et al., 2020), compressive strength of concrete incorporating recycled aggregate was predicted using M5P and ANN-based techniques. In this study, however, regression-based (linear and nonlinear regression) and ML-based (RF) models are proposed. Furthermore, the optimum percentage of recycled aggregate which could be used in concrete mixture is suggested in the present study which was not considered in the previous research. Fig. 1 demonstrated the methodology of the present research schematically.

3. Datasets

It is well-understood that ML- and regression-based methods should be applied to a compressive dataset which reflects the characteristics of the samples perfectly. The database is typically divided in two main sub-datasets: (i) training: which trains the model to find out the relationship between inputs and output and hence to predict the target output, (ii) testing dataset which is used to evaluate the accuracy of the proposed model.

The dataset collected from peer-reviewed international publications and used in the previous study (Kandiri et al., 2021) is considered for developing the prediction models. The references considered for collecting the databases, the statistical properties and histograms of the inputs and output are presented and explained extensively in the former study. Representing the above-mentioned data is avoided for the sake of shortness and the readers are referred to (Kandiri et al., 2021). It is worth mentioning that the input variables are ordinary Portland cement (OPC, kg/m^3), Sand (S, kg/m^3), coarse

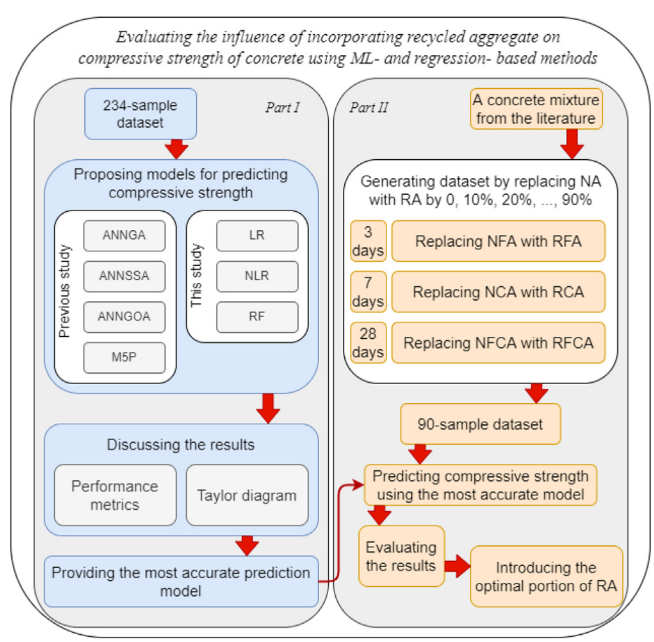


Fig. 1. The research methodology.

aggregate (CA, kg/m^3), Fine aggregate (FA, kg/m^3), water to cement ratio (W/C), superplasticizer to cement ratio (SP/C, %), recycled coarse aggregate to total coarse aggregate (CRA), testing age (days) and recycled fine aggregate to total fine aggregate (FRA) while the target output is concrete compressive strength (CS, MPa).

Understanding the correlation between each input and the output could be undoubtedly a remarkable help for proposing a proper prediction model. Among various correlation coefficients introduced so far, Pearson approach has become more common. As given in Eq. (1), Pearson correlation coefficient (PCC) is the covariance of two parameters divided by the product of their standard deviation. $\rho_{X,Y} \approx 1$ reflects the high dependency of two variables while $\rho_{X,Y} \approx 0$ stands for independent linear relationship of X and Y. Table 1 reports the obtained Pearson correlation coefficients for the variable inputs and the target output.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

The values provided in Table 1 obviously reveals that concrete age and W/C have the highest influence on the CS while CRA/CA and SP/C affect the output insignificantly. The same dependency between the mentioned parameters and CS is observed and reported in the similar experimental studies (Poon et al., 2004; Kisku et al., 2017; Zheng et al., 2018).

4. Prediction models: Background and adjustments

In the previous study, the compressive strength of concrete containing recycled aggregate was predicted by M5P tree and ANN-based models using tree optimization algorithms: Genetic algorithm (ANNGA), Slap Swarm Algorithm (ANNSSA) and Grasshopper Optimization Algorithm (ANNGOA). It should be noted that all the dataset was utilized for training and testing the models. The explanation on the proposed models could be found in the reference (Kandiri et al., 2021) and only the obtained results are used in this study. It is worth mentioning that all the parameters named in section 3 were considered as the input variables for all the models (the previous and the present study).

In the current research, an attempt has been made to use other methods of predicting compressive strength of concrete containing recycled aggregate: linear regression (LR), nonlinear regression (NLR) and Random Forest (RF). It should be explained that in all the methods considered in this study 85% and 15% of the database is used for training and testing the models, respectively.

4.1. Linear and nonlinear

Regression method could be formulated as Eq. (2), which is based on the relationship between the input variables (x_i) and the target output (y). ε reflects a random variable (error with zero mean and variation of σ^2) due to inherent variability of the system which could not be controlled by the analyzer (Abouzari et al., 2021; Huang et al., 2010).

$$y = f(x_i; \theta) + \varepsilon \tag{2}$$

Where θ are the parameters and $f(x_i;\theta)$ is a function showing the relation between inputs and output; when f is linear in θ, the output could be predicted using linear regression, a widely used inferential approach. On the other hand, nonlinear regression, which is an extension of linear regression, is utilized when a curvilinear line is used for representing the relation between inputs and outputs (nonlinear relation between f and θ) (Zhang et al., 2021; Shams et al., 2021).

4.2. Random forest

This method was proposed and introduced by Ho for the first time in 1995 by providing an algorithm for random decision forest (Fawagreh et al., 2014). Breiman (Breiman, 2001), then, used the Breiman's bagging idea and random selection of features (the method proposed by Ho and Amit and Geman (Fawagreh et al., 2014; Amit and Geman, 1997)) to develop the algorithm. The bagging method is an ensemble training method consisting of two steps; (a) bootstrap: identically distributed and independent datasets are generated by randomly resampling the original dataset, (b) aggregation: the generated datasets are considered for training the base predictors independently. Eventually, the predictions of each tree are averaged by an aggregation method and the result is considered as the target output (Chaabene et al., 2020). It is worth noting that RF is a fast, simple and high-accuracy method which could be used for both regression and classification problems (Biau, 2012).

The optimal number of trees in a forest could affect the prediction accuracy noticeably. Fig. 2 illustrates the R^2 values against the number of trees in a trial-and-error process. As could be observed in this figure, 84 trees led to the highest R^2 value.

5. Results

In this section, the results of the proposed models in this study are presented and discussed first. Then, the models' outcomes are compared to the results of the methods developed in the previous study (Kandiri et al., 2021).

5.1. Performance comparison of the LR, NLR and RF models

The predicted values obtained by LR, NLR and RF are compared to the actual values reported in the experimental tests in this section. Fig. 3 demonstrates the correlation between predicted and actual values while Fig. 4 compares the predicted compressive strength with the corresponding actual values.

The graphical comparison made and exhibited in Figs. 3 and 4 reveals that all the methods have an acceptable ability to predict compressive strength of concrete with recycled aggregate with reliable

Table 1
Pearson correlation coefficients for variable inputs and the target output.

	OPC (kg/m^3)	W/C	CA (kg/m^3)	FA (kg/m^3)	CRA	FRA	Sand (kg/m^3)	SP/C (%)	Age (day)	CS (MPa)
OPC (kg/m^3)	1									
W/C	−0.6545	1								
CA (kg/m^3)	0.2786	−0.4095	1							
FA (kg/m^3)	−0.1688	0.4244	−0.9236	1						
CRA	0.0413	−0.006	−0.0277	−0.0836	1					
FRA	−0.135	0.3212	−0.6684	0.5944	0.4911	1				
Sand (kg/m^3)	−0.2579	−0.046	0.1817	−0.4564	0.0152	−0.2044	1			
SP/C (%)	−0.2628	0.1636	0.1089	−0.1526	−0.0568	−0.0988	0.1847	1		
Age (day)	−0.1321	−0.1014	0.041	−0.0781	0.0214	−0.0505	−0.0477	0.0597	1	
CS (MPa)	**−0.1041**	**−0.4467**	**0.1705**	**−0.2524**	**−0.0507**	**−0.1863**	**0.3065**	**0.0907**	**0.4105**	**1**

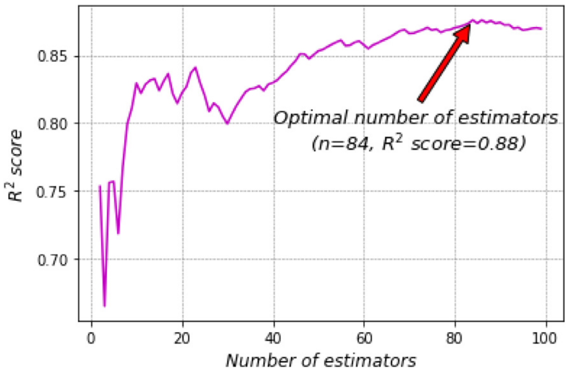


Fig. 2. R^2 score value against number of trees in the RF model.

accuracy. The model proposed based on the RF method, however, shows more accurate predicted values.

In order to discuss the results more properly, the models are quantitatively compared in terms of performance metric parameters including root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R^2) and mean absolute percentage error (MAPE) as given in Eqs. (3)–(6). Table 2 also provides the calculated performance metrics obtained using Eqs. (3)–(6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(\hat{y}_i - y_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|\hat{y}_i - y_i| \tag{4}$$

$$R^2 = 1 - \frac{\sum_i(\hat{y}_i - y_i)^2}{\sum_i(y_i - \bar{y}_i)^2} \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{6}$$

As could be figured out from Table 2, the NLR model led to the most accurate predicted values with R^2 = 98%. The RF model exhibited slightly lower accuracy in comparison to the NLR model with R^2 = 88%. The LR model, on the other hand, possessed the lowest R^2 score (=80%). It should be taken into consideration that the reported performance metrics prove the reliability of ML- and regression-based models proposed for predicting compressive strength of concrete incorporating recycled aggregate with R^2 values higher than 80%.

For a deeper discussion on the results, the model outcomes are compared in the Taylor diagram shown in Fig. 5.

It is worth explaining that Taylor diagram is known as a powerful tool which has the ability to show the accuracy of prediction models by comparing standard deviation (vertical and horizontal axis), correlation coefficient (radial lines) and RMSE (gray circular lines). The closest model to the actual value, shown herein by a red star, is introduced as the most accurate model with the similar standard deviation, higher correlation and smaller RMSE considering the actual values (Kandiri et al., 2020; Shariati et al., 2020).

As depicted in Fig. 5, the NLR model (R^2 = 0.98, std = 23.03, RMSE = 14.41) is positioned closer to the star point (actual values) compared to the other methods which confirms the accuracy of this method. Although LR and RF exhibited approximately the same std, the higher R^2 score of the RF made it more reliable than the LR method.

5.2. Performance comparison of the models proposed in both studies

In this section, the prediction models proposed in the present study are compared to those of the previous research (Kandiri et al., 2021). It is worth recalling that three ANN-based methods with different optimization methods and one M5P tree method were proposed in the former study while LR, NLR and RF approaches are utilized in this study. The dataset and the variable inputs are considered the same in both groups of the models. It should be stated that as the models of the previous study are trained and tested by all the dataset, the results of the present models are represented using all the data in the database

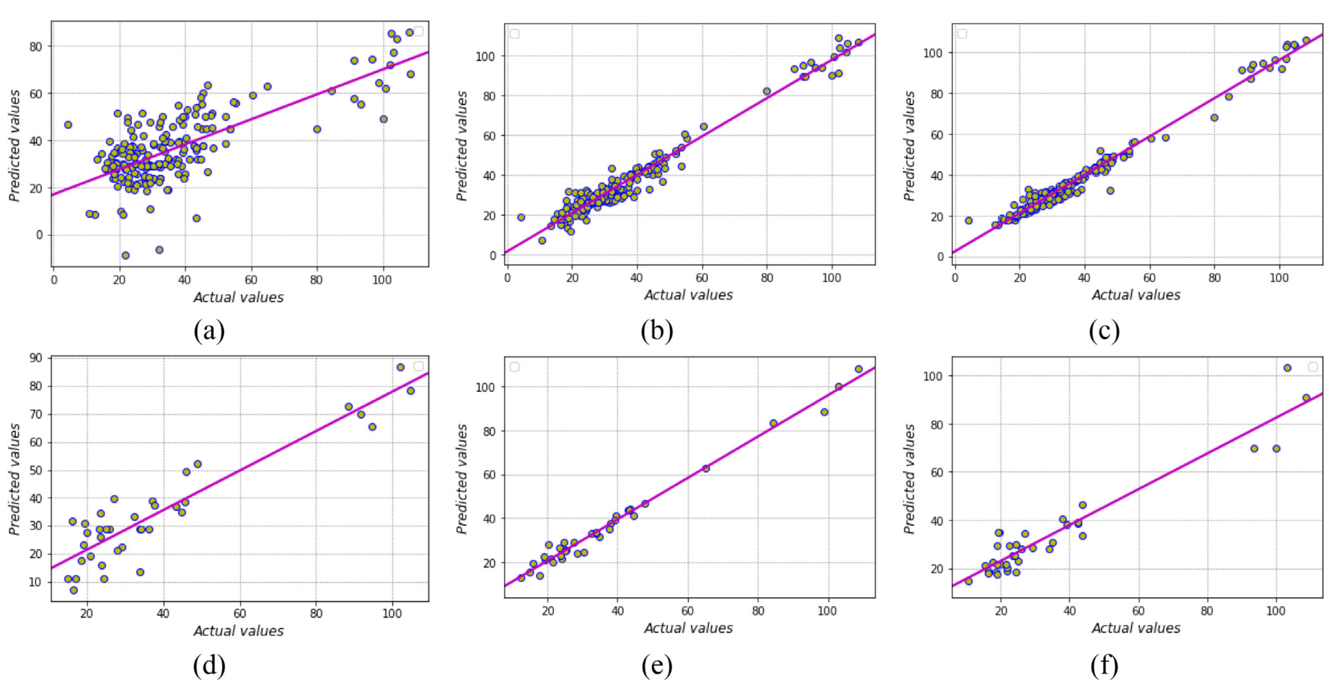


Fig. 3. Correlation between predicted and actual compressive strength in training dataset using (a) LR, (b) NLR, (c) RF and testing dataset using (d) LR, (e) NLR, (f) RF.

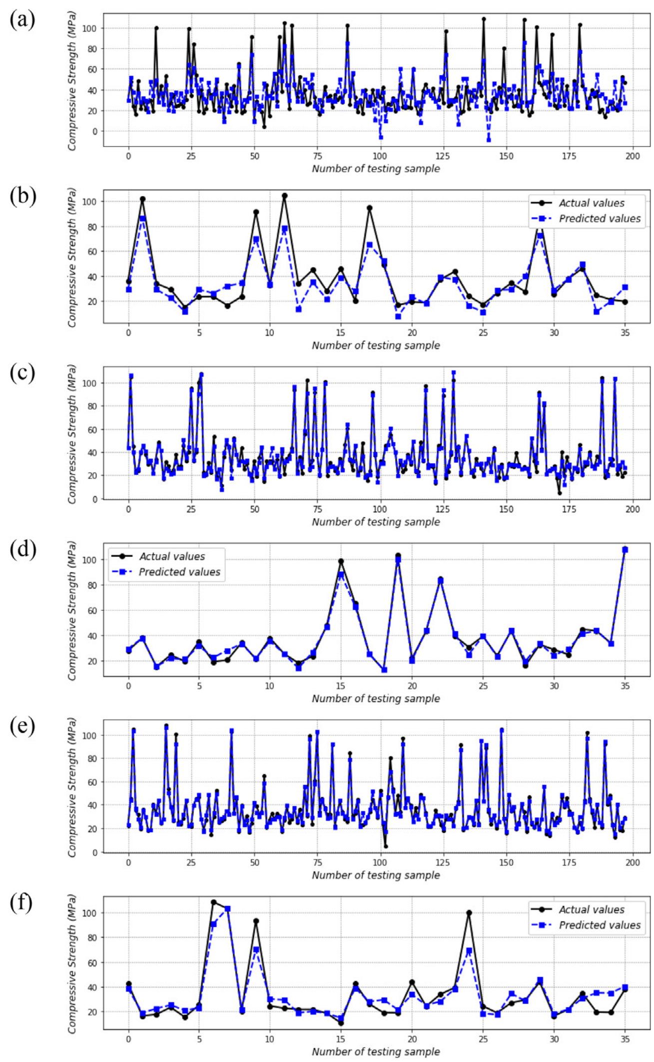


Fig. 4. Comparing predicted and actual compressive strength in training dataset using (a) LR, (b) NLR, (c) RF and testing dataset using (d) LR, (e) NLR and (f) RF.

(Figs. 3–4 and Table 2, provide the results on 85% and 15% of the dataset used for respectively training and testing).

The correlation between predicted and actual CS for all the models are illustrated in Fig. 6. The comparison between the actual CS and the corresponding CS predicted by each model is also made in Fig. 7.

The performance metrics for all the models considering all the databases are provided in Table 3.

Taking Figs. 6–7 into account and considering the values reported in Table 3, it could be stated that ANN models and RF with almost similar performance ($R^2 \approx 98\%$) are the most accurate models. NLR and M5P models with an insignificantly lower accuracy resulted in $R^2 = 97\%$ and 90%, respectively. Finally, the LR model had the lowest R^2 score (59.31%) which reflects less reliability of this model in comparison to other models.

Table 2
Performance metrics of the proposed models.

	R^2	RMSE (MPa)	MAE (MPa)	MAPE (%)
LR	0.80	11.17	8.68	25.78
NLR	**0.98**	**3.14**	**2.18**	**7.41**
RF	0.88	8.92	5.81	18.99

Fig. 8 compares the models' performance using Taylor diagram. Thanks to the visual comparison provided by Taylor diagram, it is clearly observed that the models RF, ANNGA, ANNSSA and ANNGOA are the closest models to the star point. A deeper consideration of Fig. 8 and the results reported in Table 3 clarifies that the RF model is slightly more accurate than ANN models, hence it is introduced as the best ML-based model for predicting compressive strength of CR and is used for evaluating the optimal percentage of RA in the next section. Whereas LR and M5P models exhibited less reliability in comparison to ANN and RF models, they showed still acceptable accuracy for predicting compressive strength of CR.

6. The influence of RA on concrete compressive strength

In order to evaluate the effect of RA on the compressive strength of CR, three sub-datasets, each of which containing 30 datasets are generated. A concrete mixture available in the literature (Poon et al., 2004) is chosen and natural fine aggregate, natural coarse aggregate and both natural fine and coarse aggregate are replaced with recycled fine aggregate, recycled coarse aggregate and recycled fine and coarse aggregate, respectively in a range of 0–90% with the step of 10% (0, 10%, 20%, …, 90%). The 3-day, 7-day and 28-day compressive strength of the generated data is predicted by the RF model which showed the highest prediction accuracy in the previous section.

The influence of replacing NA with RA in three different testing ages is graphically compared in Fig. 9 and the quantitative results are reported in Table 4. It should be explained that $\Delta CS_i = (CS_i - CS_0)/CS_0$ where i represents the RA replacement.

Taking Fig. 9 into account, it could be claimed that regardless of the RA type (RFA, RCA or RFCA), replacing natural aggregate with recycled aggregate reduces concrete compressive strength. The same results reported in the experimental examinations on the behavior of concrete incorporating RA (Tam et al., 2018; Wang et al., 2021; Kisku et al., 2017; Zheng et al., 2018), proves the high accuracy of the values predicted by RF model. Furthermore, based on the graphical comparison made in Fig. 8, replacing NA with RA up to almost 30%, reduces CS noticeably. Then, the CS reduces slightly for replacement proportions of *30–90%*. The rate of strength reduction is heavily dependent on many factors such as aggregate type and testing age. The results of similar studies confirm slight changes of compressive strength for replacement portion larger than 30% (Abid et al., 2018; Vo et al., 2021; Sadeghi-Nik et al., 2019; Poon et al., 2004).

As far as aggregate type is concerned, it could be claimed that replacing natural coarse aggregate by recycled coarse aggregate could affect concrete strength more than fine or both fine and coarse replacement. As also provided in Table 4 (28-day testing age), strength reduction reported for concrete containing RCA is in the range of 9.88–35.68% while those of concrete with RFA and RFCA are respectively 4.98–16.15% and 9.83–34.06%. As a result, replacing natural coarse aggregate by recycled coarse aggregate could lead to remarkable decrease in CS which might affect structural applicability of concrete negatively. On the other hand, the influence of replacing FA by RA on concrete strength is limited. The same results have been reported in similar experimental study (Aliabdo et al., 2014).

Taking the effect of testing age into account, it could be stated that for the concrete containing coarse or both fine and coarse recycled aggregate, the changes of 3-day and 7-day compressive strength is less than 28-day compressive strength. Considering the numerical compressive strength reported in Table 4, the 3- and 7-day strength values vary in the range of 4.76–16.90% and 6.47–13.26, respectively, while 28-day strength alters in the range of and 9.83–34.06%. On the other hand, for the concrete with fine recycled aggregate the reduction in compressive strength of 3-day testing (3.15–29.27) is higher than 7- (3.76–6.28) and 28-day testing (4.98–16.15). For easier comparison of the CS changes in different ages, Fig. 10 is presented.

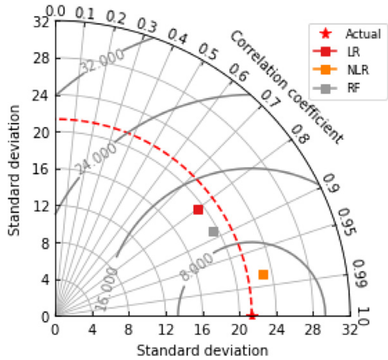


Fig. 5. Taylor diagram for comparing LR, NLR and RF models.

It should be taken into consideration that the 28-day compressive strength is generally considered for structural design purposes and hence is of importance. Based on the results of this study, replacing NFA with RFA could be suggested because of the limiter concrete strength reduction in comparison to those of RCA and RFCA.

7. Summery and conclusions

Nowadays, replacing natural aggregate with recycled aggregate has been increasingly interesting because of its economic and environmental assets. In this research, therefore, an attempt has been made to assess the effect of incorporating recycled fine aggregate, recycled coarse aggregate and recycled fine and coarse aggregate on concrete compressive strength using ML-based methods. To this aim, the paper is organized in two main parts: (a) LR, NLR and RF prediction models are proposed in the present study, and their results are compared to those of ANNGA, ANNGOA, ANNSSA and M5P models developed in the previous study (Kandiri et al., 2021). Otherwise stated, random forest and regression-based (linear and nonlinear) models are developed in this study while M5P and ANN-based techniques were utilized in the previous study (Kandiri et al., 2021). The most accurate model (RF which was proposed in this study) is introduced through performance metrics and Taylor diagram to be used in the second part; (b) a concrete mixture is selected from the literature for generating 90 datasets by replacing NFA, NCA and NFCA with RFA, RCA and RFCA, respectively, each of which in three different testing ages (3, 7 and 28 days). The concrete compressive strength of the dataset is predicted by the high-accuracy proposed RF model. The final remarks are:

- Regression- and ML- based methods have an acceptable ability to learn the relationship between concrete mixture parameters and compressive strength. They could be considered as a simple, quick and reliable alternative approach for costly and time-consuming experimental tests carried out to determine compressive strength of concrete containing recycled aggregate.
- The nonlinear regression, random forest and ANN- based models exhibited higher accuracy in comparison to linear regression and M5P models.
- Replacing natural aggregate with recycled aggregate, regardless of the aggregate type and concrete age, decreases concrete compressive strength. Aggregate type and concrete age, however, affect the concrete strength significantly.

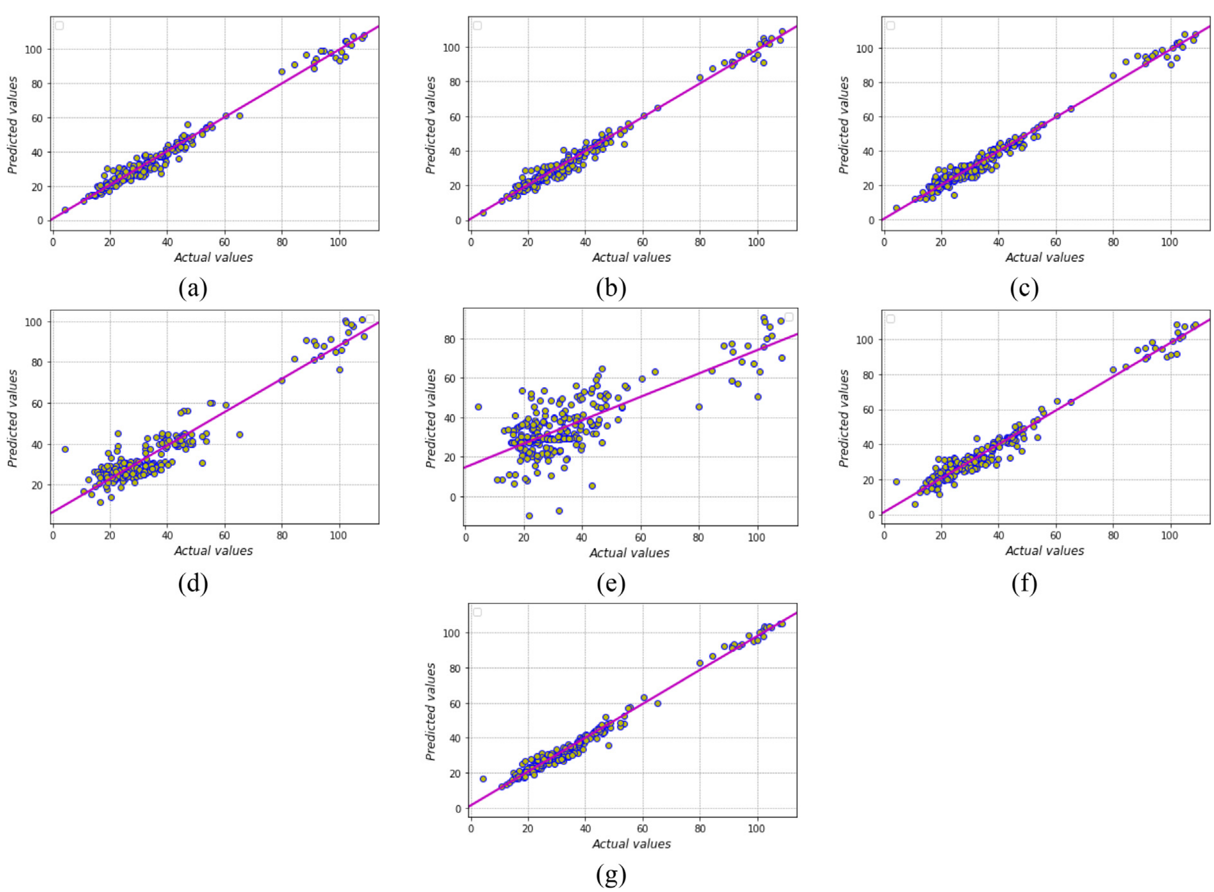


Fig. 6. Correlation between predicted and actual compressive strength obtained by (a) ANNGA, (b) ANNSSA, (c) ANNGOA, (d) M5P, (e) LR, (f) NLR and (g) RF.

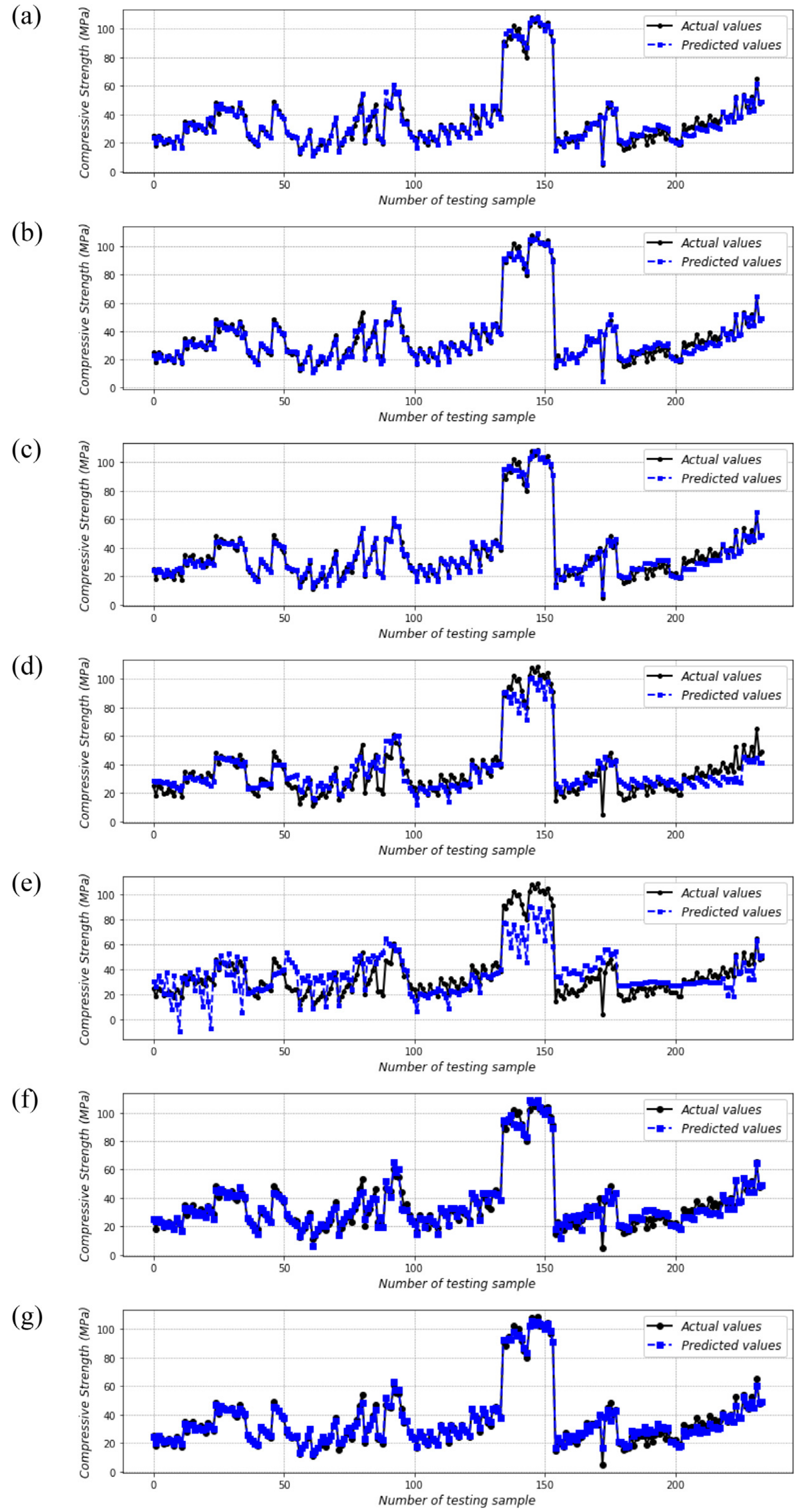


Fig. 7. Comparing the predicted and actual compressive strength obtained by (a) ANNGA, (b) ANNSSA, (c) ANNGOA, (d) M5P, (e) LR, (f) NLR and (g) RF.

- In terms of aggregate type (size), replacing coarse aggregate with recycled aggregate led to more reduction of compressive strength rather than fine aggregate or both fine and coarse aggregate replacement.
- Taking concrete testing age into account, for the concrete with fine recycled aggregate the reduction in 3-day compressive strength is higher than 7- and 28-day compressive strength while for the concrete incorporating coarse or both fine and coarse recycled concrete, the decrease in 28-day compressive strength is higher than that of 3- and 7-day.
- Replacing natural aggregate with recycled aggregate up to 30%, reduces concrete compressive strength noticeably and then it decreases slightly for replacement proportions of 30–90%.

Table 3
Performance metrics of all the proposed models.

	R^2 (%)	RMSE (MPa)	MAE (MPa)	MAPE (%)
ANNGA	98.01	2.94	2.09	6.80
ANNSSA	98.41	2.73	1.89	6.22
ANNGOA	98.01	3.02	2.23	7.79
M5P	89.68	7.10	5.50	21.46
LR	59.31	13.59	10.30	36.75
NLR	96.75	3.84	2.73	10.46
RF	98.48	2.63	1.83	7.16

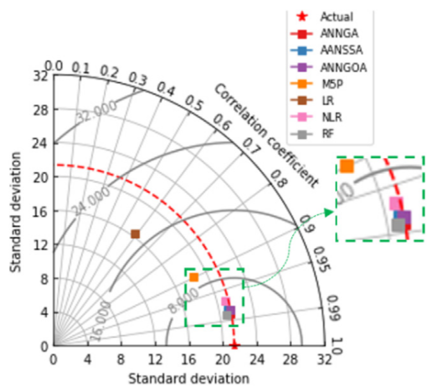


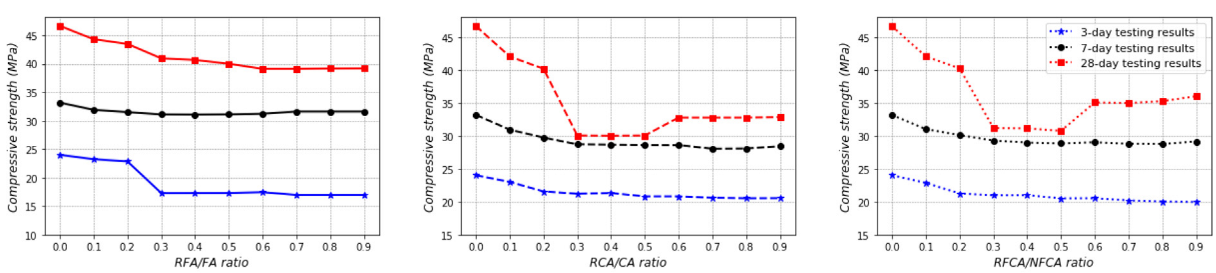
Fig. 8. Taylor diagram for comparing all the models proposed in the present and previous study.

8. Recommendations and limitations

Since the 28-day compressive strength is generally used for designing structures and taking the reported value in Table 4 into account, following recommendations could be made:

- Replacing both of fine and coarse natural aggregate with recycled aggregate might reduce concrete compressive strength significantly and hence is not recommended.
- Incorporating recycled fine aggregate could decrease concrete compressive strength slightly and is preferred than coarse or both fine and coarse aggregate.
- Because of the environmental and economical benefits of using recycled aggregate, and considering the last bullet of conclusions, using RFA up to 90% in concrete mixtures does not cause any issues if the compressive strength reduction is taken into consideration in structural design and concrete application. However, disadvantages of incorporating recycled aggregate namely reduction in modulus of elasticity, ductility, density, durability and its remarkable influence on workability, shrinkage, water absorption and air content of concrete should be given especial attention in the case of replacing natural aggregate with recycled aggregate.

Finally, it should be noted that other parameters (e.g., flexural strength, splitting tensile strength, water absorption, modulus of elasticity) might be affected noticeably by replacing NA with RA. Furthermore, factors such as old mortar content and old mortar property of recycled coarse aggregate which have an undeniable influence of compressive strength of concrete incorporating RA are not considered in

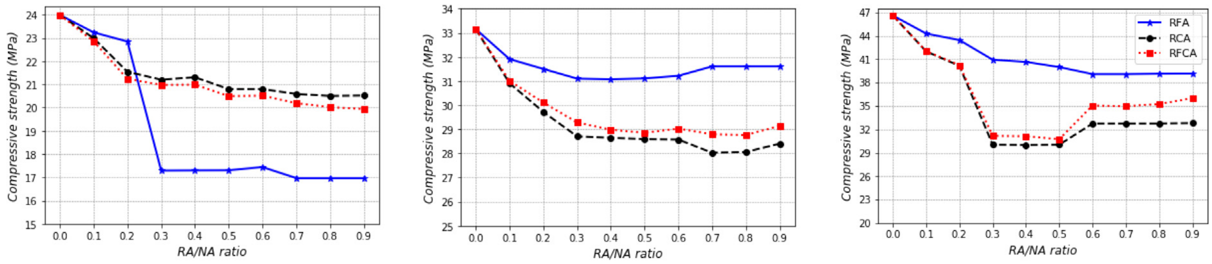


(a) (b) (c)

Fig. 9. Compressive strength of concrete with different replacement portion of (a) RFA, (b) RCA and (c) RFCA in different ages.

Table 4
Compressive strength of concrete containing different portions of RFA, RCA and RFCA.

RA Portion (%)	3-day CS (MPa)						7-day CS (MPa)						28-day CS (MPa)					
	RFA		RCA		RFCA		RFA		RCA		RFCA		RFA		RCA		RFCA	
	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)	CS (MPa)	ΔCS_i (%)
0	23.99	***	23.99	***	23.99	***	33.15	***	33.15	***	33.15	***	46.62	***	46.62	***	46.62	***
10	23.24	−3.15	22.99	−4.18	22.85	−4.76	31.91	−3.76	30.91	−6.77	31.01	−6.47	44.30	−4.98	42.02	−9.88	42.04	−9.83
20	22.85	−4.77	21.54	−10.21	21.24	−11.49	31.50	−4.98	29.72	−10.36	30.11	−9.19	43.47	−6.77	40.16	−13.87	40.24	−13.70
30	17.29	−27.93	21.20	−11.64	20.98	−12.57	31.10	−6.20	28.70	−13.43	29.28	−11.68	40.95	−12.18	30.03	−35.58	31.17	–33.14
40	17.30	−27.90	21.31	−11.20	20.99	−12.53	31.07	−6.28	28.64	−13.61	28.98	−12.60	40.66	−12.78	29.99	−35.68	31.12	–33.25
50	17.31	−27.88	20.80	−13.32	20.50	−14.57	31.11	−6.18	28.59	−13.77	28.85	−12.99	39.99	−14.22	30.03	−35.59	30.74	−34.06
60	17.44	−27.30	20.80	−13.32	20.52	−14.50	31.22	−5.85	28.57	−13.82	29.02	−12.46	39.10	−16.15	32.75	−29.75	35.06	−24.80
70	16.97	−29.27	20.59	−14.20	20.19	−15.85	31.61	−4.67	28.03	−15.47	28.79	−13.17	39.10	−16.15	32.75	−29.75	34.97	−24.99
80	16.97	−29.27	20.50	−14.54	20.02	−16.57	31.61	−4.67	28.06	−15.37	28.76	−13.26	39.15	−16.02	32.75	−29.75	35.25	−24.39
90	16.97	−29.27	20.52	−14.47	19.94	−16.90	31.61	−4.67	28.40	−14.34	29.14	−12.12	39.17	−15.98	32.81	−29.62	36.01	–22.77



(a) (b) (c)

Fig. 10. Compressive strength changes in different ages: (a) 3 days, (b) 7 days and (c) 28 days.

this research. Thus, further studies evaluating the influence of the above-mentioned parameters are needed in order to reach more reliable and practical conclusions on the optimal percentage of RA.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abid, Sallal R., Nahhab, Ali H., Al-aayedi, Husam K.H., Nuhair, Athraa M., 2018. Expansion and strength properties of concrete containing contaminated recycled concrete aggregate. Case Stud. Constr. Mater. 9, e00201. https://doi.org/10.1016/j.cscm.2018.e00201.

Abouzari, M. et al, 2021. Estimating the chemical oxygen demand of petrochemical wastewater treatment plants using linear and nonlinear statistical models–A case study. Chemosphere 270, 129465.

Ahmadi, M. et al, 2020. New empirical approach for determining nominal shear capacity of steel fiber reinforced concrete beams. Constr. Build. Mater. 234, 117293.

Aliabdo, Ali A., Abd-Elmoaty, Abd-Elmoaty M., Hassan, Hani H., 2014. Utilization of crushed clay brick in concrete industry. Alexandria Eng. J. 53 (1), 151–168.

Amit, Yali, Geman, Donald, 1997. Shape quantization and recognition with randomized trees. Neural Comput. 9 (7), 1545–1588.

Bai, G. et al, 2020. An evaluation of the recycled aggregate characteristics and the recycled aggregate concrete mechanical properties. Constr. Build. Mater. 240, 117978.

Biau, G., 2012. Analysis of a random forests model. J. Mach. Learn. Res. 13, 1063–1095.

Breiman, L., 2001. Random forests. Mach. Learn. 45 (1), 5–32.

Bypour, M., Kioumarsi, M., Yekrangnia, M., 2021. Shear capacity prediction of stiffened steel plate shear walls (SSPSW) with openings using response surface method. Eng. Struct. 226, 111340.

Cantero, B. et al, 2020. Mechanical behaviour of structural concrete with ground recycled concrete cement and mixed recycled aggregate. J. Cleaner Prod. 275, 122913.

Chaabene, W.B., Flah, M., Nehdi, M.L., 2020. Machine learning prediction of mechanical properties of concrete: Critical review. Constr. Build. Mater. 260, 119889.

Chaboki, Hamid Reza, Ghalehnovi, Mansour, Karimipour, Arash, de Brito, Jorge, 2018. Experimental study on the flexural behaviour and ductility ratio of steel fibres coarse recycled aggregate concrete beams. Constr. Build. Mater. 186, 400–422.

Dabiri, H., Kheyroddin, A., 2017. An analytical study into the seismic behavior of RC pier with elastomeric materials. Asian J. Civil Eng. (BHRC) 18 (7), 1183–1193.

Dabiri, H., Sharbatdar, M.K., Kavyani, A., Baghdadi, M., 2018. The influence of replacing sand with waste glass particle on the physical and mechanical parameters of concrete. Civil Eng. J. 4 (7), 1646. https://doi.org/10.28991/cej-03091101.

Deng, Fangming, He, Yigang, Zhou, Shuangxi, Yu, Yun, Cheng, Haigen, Wu, Xiang, 2018. Compressive strength prediction of recycled concrete based on deep learning. Constr. Build. Mater. 175, 562–569.

Duan, Jin, Asteris, Panagiotis G., Nguyen, Hoang, Bui, Xuan-Nam, Moayedi, Hossein, 2021. A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model. Eng. Comput. 37 (4), 3329–3346.

Evangelista, L., de Brito, J., 2007. Mechanical behaviour of concrete made with fine recycled concrete aggregates. Cem. Concr. Compos. 29 (5), 397–401.

Fawagreh, K., Gaber, M.M., Elyan, E., 2014. Random forests: from early developments to recent advancements. Syst. Sci. Control Eng. Open Access J. 2 (1), 602–609.

Flah, Majdi, Nunez, Itzel, Ben Chaabene, Wassim, Nehdi, Moncef L., 2021. Machine learning algorithms in civil structural health monitoring: A systematic review. Arch. Comput. Methods Eng. 28 (4), 2621–2643.

Gao, Chang, Huang, Liang, Yan, Libo, Jin, Ruoyu, Kasal, Bohumil, 2019. Strength and ductility improvement of recycled aggregate concrete by polyester FRP-PVC tube confinement. Compos. B Eng. 162, 178–197.

Gravina, R.J. et al, 2021. Assessment of the variability and uncertainty of using post-customer plastics as natural aggregate replacement in concrete. Constr. Build. Mater. 273, 121747.

Han, T. et al, 2020. An ensemble machine learning approach for prediction and optimization of modulus of elasticity of recycled aggregate concrete. Constr. Build. Mater. 244, 118271.

Huang, H.-H., Hsiao, C.K., Huang, S.-Y., 2010. In: International Encyclopedia of Education. Elsevier, pp. 339–346. https://doi.org/10.1016/B978-0-08-044894-7.01352-X.

Ismail, Sallehan, Ramli, Mahyuddin, 2013. Engineering properties of treated recycled concrete aggregate (RCA) for structural applications. Constr. Build. Mater. 44, 464–476.

Kaish, A. et al, 2021. Effects of different industrial waste materials as partial replacement of fine aggregate on strength and microstructure properties of concrete. J. Build. Eng. 35, 102092.

Kandiri, A., Golafshani, E.M., Behnood, A., 2020. Estimation of the compressive strength of concretes containing ground granulated blast furnace slag using hybridized multi-objective ANN and salp swarm algorithm. Constr. Build. Mater. 248, 118676.

Kandiri, A., Sartipi, F., Kioumarsi, M., 2021. Predicting compressive strength of concrete containing recycled aggregate using modified ann with different optimization algorithms. Appl. Sci. 11 (2), 485.

Kang, Ma, Weibin, Li, 2018. Effect of the aggregate size on strength properties of recycled aggregate concrete. Adv. Mater. Sci. Eng. 2018, 1–8.

Kazmi, S.M.S. et al, 2020. Effect of recycled aggregate treatment techniques on the durability of concrete: a comparative evaluation. Constr. Build. Mater. 264, 120284.

Kioumarsi, Mahdi, Azarhomayun, Fazel, Haji, Mohammad, Shekarchi, Mohammad, 2020. Effect of shrinkage reducing admixture on drying shrinkage of concrete with different w/c ratios. Materials 13 (24), 5721. https://doi.org/10.3390/ma13245721.

Kisku, N., Joshi, H., Ansari, M., Panda, S.K., Nayak, Sanket, Dutta, Sekhar Chandra, 2017. A critical review and assessment for usage of recycled aggregate as sustainable construction material. Constr. Build. Mater. 131, 721–740.

Kou, Shi-Cong, Poon, Chi-Sun, Etxeberria, Miren, 2011. Influence of recycled aggregates on long term mechanical properties and pore size distribution of concrete. Cem. Concr. Compos. 33 (2), 286–291.

Kou, Shi-Cong, Poon, Chi-Sun, Wan, Hui-Wen, 2012. Properties of concrete prepared with low-grade recycled aggregates. Constr. Build. Mater. 36, 881–889.

Manzi, S., Mazzotti, C., Bignozzi, M.C., 2013. Short and long-term behavior of structural concrete with recycled concrete aggregate. Cem. Concr. Compos. 37, 312–318.

Matar, P., Barhoun, J., 2020. Effects of waterproofing admixture on the compressive strength and permeability of recycled aggregate concrete. J. Build. Eng. 32, 101521.

Mi, R. et al, 2020. Utilizing recycled aggregate concrete in sustainable construction for a required compressive strength ratio. J. Cleaner Prod. 276, 124249.

Nunez, I., Nehdi, M.L., 2021. Machine learning prediction of carbonation depth in recycled aggregate concrete incorporating SCMs. Constr. Build. Mater. 287, 123027.

Poon, C.S., Shui, Z.H., Lam, L., Fok, H., Kou, S.C., 2004. Influence of moisture states of natural and recycled aggregates on the slump and compressive strength of concrete. Cem. Concr. Res. 34 (1), 31–36.

Rahal, Khaldoun, 2007. Mechanical properties of concrete with recycled coarse aggregate. Build. Environ. 42 (1), 407–415.

Rahla, K.M., Mateus, R., Bragança, L., 2019. Comparative sustainability assessment of binary blended concretes using Supplementary Cementitious Materials (SCMs) and Ordinary Portland Cement (OPC). J. Cleaner Prod. 220, 445–459.

Ramkumar, K. et al, 2020. A review on performance of self-compacting concrete–use of mineral admixtures and steel fibres with artificial neural network application. Constr. Build. Mater. 261, 120215.

Sadeghi-Nik, Aref, Berenjian, Javad, Alimohammadi, Sahar, Lotfi-Omran, Omid, Sadeghi-Nik, Adel, Karimaei, Mahmood, 2019. The effect of recycled concrete aggregates and metakaolin on the mechanical properties of self-compacting concrete containing nanoparticles. Iranian J. Sci. Technol. Trans. Civil Eng. 43 (S1), 503–515.

Salehi, Hadi, Burgueño, Rigoberto, 2018. Emerging artificial intelligence methods in structural engineering. Eng. Struct. 171, 170–189.

Shams, S.R. et al, 2021. The evaluation on artificial neural networks (ANN) and multiple linear regressions (MLR) models for predicting SO2 concentration. Urban Clim. 37, 100837.

Shariati, M., et al., 2020. A novel hybrid extreme learning machine–grey wolf optimizer (ELM-GWO) model to predict compressive strength of concrete with partial replacements for cement. Eng. Comput., 1–23.

Steyn, Z. et al, 2021. Concrete containing waste recycled glass, plastic and rubber as sand replacement. Constr. Build. Mater. 269, 121242.

Sun, Han, Burton, Henry V., Huang, Honglan, 2021. Machine learning applications for building structural design and performance assessment: state-of-the-art review. J. Build. Eng. 33, 101816. https://doi.org/10.1016/j.jobe.2020.101816.

Tam, Vivian W.Y., Tam, C.M., Le, K.N., 2007. Removal of cement mortar remains from recycled aggregate using pre-soaking approaches. Resour. Conserv. Recycl. 50 (1), 82–101.

Tam, Vivian W.Y., Soomro, Mahfooz, Evangelista, Ana Catarina Jorge, 2018. A review of recycled aggregate in concrete applications (2000–2017). Constr. Build. Mater. 172, 272–292.

Thomas, C. et al, 2020. Macro-and micro-properties of multi-recycled aggregate concrete. J. Cleaner Prod. 245, 118843.

Vieira, L.d.B.P., de Figueiredo, A.D., John, V.M., 2020. Evaluation of the use of crushed returned concrete as recycled aggregate in ready-mix concrete plant. J. Build. Eng. 31, 101408.

Vo, Duy-Hai, Hwang, Chao-Lung, Tran Thi, Khanh-Dung, Liao, Min-Chih, Yehualaw, Mitiku Damtie, 2021. Engineering performance of high-content MgO-Alkali-activated slag mortar incorporating fine recycled concrete aggregate and fly ash. J. Mater. Cycles Waste Manage. 23 (2), 778–789.

Wang, B. et al, 2021. A Comprehensive Review on Recycled Aggregate and Recycled Aggregate Concrete. Resour. Conserv. Recycl. 171, 105565.

Xiao, R. et al, 2020. Analytical investigation of phase assemblages of alkali-activated materials in CaO-SiO2-Al2O3 systems: The management of reaction products and designing of precursors. Mater. Des. 194, 108975.

Xiao, R., Jiang, X.i., Wang, Y., He, Q., Huang, B., 2021. Experimental and thermodynamic study of alkali-activated waste glass and calcium sulfoaluminate cement blends: shrinkage, efflorescence potential, and phase assemblages. J. Mater. Civ. Eng. 33 (11), 04021312. https://doi.org/10.1061/(ASCE)MT.1943-5533.0003941.

Xiao, Jianzhuang, Li, Jiabin, Zhang, Ch., 2005. Mechanical properties of recycled aggregate concrete under uniaxial loading. Cem. Concr. Res. 35 (6), 1187–1194.

Xu, Jinjun, Zhao, Xinyu, Yu, Yong, Xie, Tianyu, Yang, Guosong, Xue, Jianyang, 2019. Parametric sensitivity analysis and modelling of mechanical properties of normal- and high-strength recycled aggregate concrete using grey theory, multiple nonlinear regression and artificial neural networks. Constr. Build. Mater. 211, 479–491.

Yang, J., Du, Q., Bao, Y., 2011. Concrete with recycled concrete aggregate and crushed clay bricks. Constr. Build. Mater. 25 (4), 1935–1945.

Zhang, J. et al, 2020. A hybrid intelligent system for designing optimal proportions of recycled aggregate concrete. J. Cleaner Prod. 273, 122922.

Zhang, K. et al, 2021. Production capacity identification and analysis using novel multivariate nonlinear regression: Application to resource optimization of industrial processes. J. Cleaner Prod. 282, 124469.

Zheng, Chaocan, Lou, Cong, Du, Geng, Li, Xiaozhen, Liu, Zhiwu, Li, Liqin, 2018. Mechanical properties of recycled concrete with demolished waste concrete aggregate and clay brick aggregate. Results Phys. 9, 1317–1322.