International Journal of Advanced Engineering and Technology
www.newengineeringjournal.com
ISSN: 2456-7655
Received: 15-08-2021, Accepted: 01-09-2021, Published: 17-09-2021
Volume 5, Issue 2, 2021, Page No. 16-22

Interrelation on the attributes of recycled aggregate concrete and its strength prediction using gradient boosting

Shamili Syed Rizvon[1*], Karthikeyan Jayakumar[2]

[1] Research Scholar, Department of Civil Engineering, National Institute of Technology, Tiruchirappalli, Tamil Nadu, India
[2] Associate Professor, Department of Civil Engineering, National Institute of Technology, Tiruchirappalli, Tamil Nadu, India

Abstract

Prediction of concrete strength is essential for proportioning new mixtures and quality assurance of the concrete produced. Researches have been made to predict the above, using statistical approaches like Linear Regression, Machine Learning approaches like Artificial Neural Network. The goal of this paper is to compare the aforementioned approaches with Gradient Boosting algorithms, in this case, extreme gradient boosting (XGB). The data for analysis and experimentation was taken from 7, 28, and 56 days of curing period across several parameters with the readings collected in the laboratory under standard controlled conditions. The resultant data was fed in algorithms developed in Python for predicting the compressive strength of recycled aggregate concrete. Also to the relationship for different cement content (300kg/m^3, 350kg/m^3, 400kg/m^3, 450kg/m^3) with varying w/c and different curing ages were developed. From the observations made, 400kg/m^3 of cement content achieves 40.16MPa which is 17.1%, 24.5% and 17.2% greater than 300kg/m^3, 350kg/m^3 and 450kg/m^3. In the case of the statistical approach, the XGB algorithm helps us attain more accurate predictions which are 9.5% and 6.4% greater than Linear Regression and Artificial Neural Networks respectively.

Keywords: linear regression, artificial neural network, gradient boosting, recycled aggregate concrete, compressive strength

Introduction

Due to the huge scale demolitions of structures, an enormous measure of debris is created everywhere in the world, which causes significant environmental contaminations including a disposal issue. In India, about 14.5 million tons of solid debris are created every year from development businesses, which incorporate waste sand, rock, bitumen, blocks, stonework, and cement. The land region needed for filling this immense measure of trash is identical to a collection of waste. Aggregates acquired from the destruction of concrete members and structures, by and large, are alluded to as Recycled Aggregates (RA). These hardened concretes can be squashed and reused as coarse aggregate in the creation of new concrete, prompting a specific sort of concrete known as "green concrete". In this, natural coarse aggregates are partially or completely supplanted by reused aggregates got from construction and demolition waste (CDW) subsequently diminishing the utilization of normal aggregates and the issue of mining. Nonetheless, in contrast with normal aggregates (NA), the nature of CDW aggregate is poor, which confines its utilization in assortments of development applications. Various researches highlight that Recycled coarse aggregates (RCAs) are more porous than natural aggregates (NA). This higher porosity is attributed to the presence of capillary pores, micro-cracks which is accessible to water. Due to the low thickness and high porosity of RA, Recycled aggregate concrete (RAC) probably could be more vulnerable than typical normal aggregate concrete (NAC) [12, 13] and the compressive strength of RAC could be extensively not exactly that of NAC [14-16]. The most outrageous substitution of NA by RA was now bound to under half in different countries to guarantee the attributes of concrete [16, 17]. The primary attributes of RAC were begun to think after the 2000s to apply RAC into authentic arranging. It is shown that an outrageous strain of RAC diminished with the improvement of the substitution by RA from the inevitable results of axial compression test [18], though the substitution of half NA by RA showed a slight impact on aversion from the shear test consequences of RAC beams [19]. Also, it is recognized the low Young's modulus and high shortcoming of RAC was the tremendous volume substance of new and old substantial mortar, particularly the immense portion of frail old mortar in RA [20, 21]. The attributes of RA impacted by the porous ITZ may be the most vulnerable point in RAC considering the way that the strength of followed mortar in RA is lower than that in NA [22, 23].

Therefore, the determination of properties of RCA's is essential for construction. In this manner, pieces of investigation have been coordinated to expect significant compressive strength. The improvement business is accepted to be overpowered with asset planning, hazard the executives, and arrangement challenges which consistently end in style absconds, project conveyance delays, value invades, and composed understanding questions. These challenges have provoked assessment inside the utilization of state-of-the-art AI estimations like significant sorting out some way to assist with decisive and prescriptive examination of causes and preventive measures. As such to work on the investigation, in the same way, lessen the cost and time needed for testing, the models dependent upon test data expecting the CS with an agreeable degree of flaw might be maintained [9, 11]. Experts in the improvement business have made a couple of shocking undertakings to remain mindful of the speed of applying significant learning [24]. Counterfeit Neural Networks, Regression examination is a bit of the method that was executed to anticipate the compressive strength of RAC. The relationship between obliterated considerable attributes and strength of their RAC was set up using backslide examination [25]. Furthermore, other data-driven models like Linear Regression and Model Trees were used to show CSC also, information-driven models show better precision when non-dimensional boundaries were utilized as extra info boundaries [26, 3]. During the constant years, a remarkable idea by the experts of material science has been extended unequivocally for the 28-days CSC because of material mechanical property [27-33], while, for the check of novel delicate processing frameworks it is utilized as an essential model [34]. As a powerful technique, in regression analysis, the relationship between a reaction variable which is the dependent variable, and at least one independent variable are used for evaluation [35]. XG Boost is an extreme inclination boosting calculation which is an important gadget to foresee the compressive strength of cement invaluable primary structure applications [36].

Material properties

Recycled aggregates employed in the current investigation were acquired from a demolished building in Tiruchirappalli, Tamil Nadu. Different samples of RCA were taken from the same demolished building. Totally 37 bags of samples were collected and arranged. From each bag, 4 samples were taken for these tests, and an average value of results was calculated. The different number of trials for each sample bag notated as B1, B2, and B3…up to B37. According to IS: 383-1970 [39] sand zone was conformed as grading zone-IV. Table 1 shows the results of physical properties.

Fineness Modulus (FM)

The particle size distribution of coarse aggregates was resolved with the assistance of sieve analysis. This was finished by sieving the aggregates according to IS 2386:2002 [40]. In this strategy, various sieves as normalized by the IS code were utilized and made aggregates to pass through them and hence collected distinctive sizes particles leftover various sieves.

Specific gravity (SG)

To measure the strength and quality of the coarse aggregates specific gravity test is considered. Specific gravity test is carried out with the help of a pycnometer. IS 2386 [42].

Water Absorption (WA)

Water absorption of coarse aggregates was directed as per IS 2386 [40]. The water absorption limit of CDW aggregate is higher than that of normal aggregate as RCA is made out of cement paste, which is permeable naturally and consequently can retain high measures of water [37, 38, 42]. The variation of water retention capacity is because of the variation of cement paste content and other components such as crushed clay brick and tiles [43]. Physical properties such as Fineness modulus (FM), Specific gravity (SG), and Water absorption (WA) have been determined for different bags of RCA.

Table 1: Physical properties of different materials used

S.No	Material	Property	value
1	RCA	FM	7.72
		SG	2.55
		% WA	1.95
2	NCA	FM	7.23
		SG	2.76
		% WA	0.36
3	R Sand	FM	1.92
		SG	2.54
		% WA	4
4	Cement	SG	3.13
5	Super plasticizer (Conplast SP 430)	SG	1.2

Modelling Techniques

In the data-driven model, the prediction model which is known as an estimator uses the measured data as an estimator, which uses the measured data as an input variable. The prediction model involves a step called the “training step” which helps the model to learn from a collection of training patterns. In this current study, three different models have been used for the prediction of the compressive strength of recycled coarse aggregate concrete. They are multi linear regression artificial neural network, XG Boost. The performances of these models are based on the coefficient of determination of R^2.

Artificial neural network (ANN)

ANN is made up of neurons, joined together by synapses (nodes in machine learning terminology), where the computational tasks are performed by these neurons. Synapses are those which link the neurons together by linking their input and output. A neuron is a marginally more unpredictable article that can be associated with at least one information neurotransmitter to at least one yield neural connections. Hence, the design of the neural organization is characterized so that the neuron and neurotransmitters are connected. Figure 1 shows the neural network architecture.

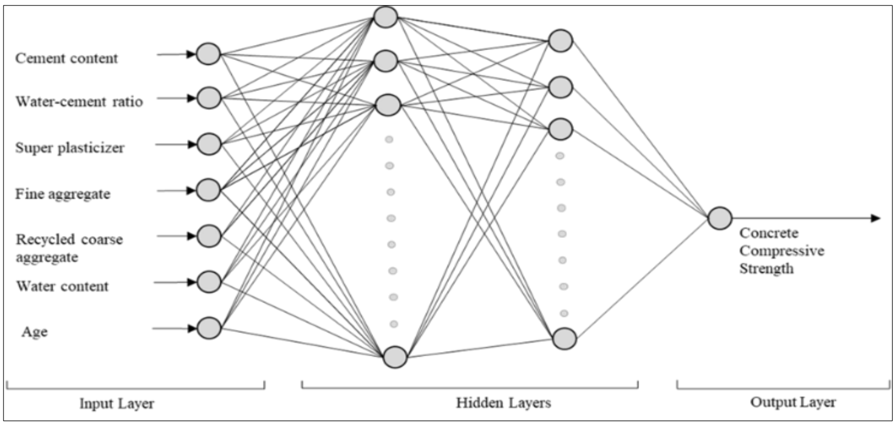


Fig 1: Architecture of Neural Network

Neurons in the network are generally arranged in layers namely input layers, hidden layers, and the output layer which is the last layer of the neuron. Neural organization can be prepared to play out a specific capacity by changing the values (weights) between elements. The output value will be equal to their input multiplied by some weight value. These normal kinds of neuron are recorded underneath

1. Input neuron or Input layer: This is the layer where input esteems are given to the network. The output of each input neurons will be equivalent to enter esteem appointed to it.
2. Hidden neuron or Hidden layer: These neurons give the organization ability to perform calculations, the yield of this neuron is equivalent to the amount of its information duplicated by an activation function.
3. Output neuron or Output layer: This neuron helps in reading the output esteems.
4. In this current study, the ANN model algorithm is taken from the tensor flow library. Tensor stream is an open-source programming library for performing mathematical calculations.

Multilinear regression (MLR)

It is a statistical tool utilized to correlate among one or more variables. The regression model is a process of fitting the models to the data. If the model has one independent variable or predictor, it is called simple linear regression. If the model has two or more input variables, that is called multiple linear regression. Essentially, MLR gauges the degree of connection among input and output factors and decides their relationship structure too. The least-square approach is mostly fitted in linear regression, however, by using other methods like adjusted R^2, RMSE is used to fit the model.

$$Y = \beta_0 + \sum_{i=1}^{m} \beta_i X_i + \varepsilon \quad (1)$$

Y=dependent variable represents concrete compressive strength
β_0=constant
β_i=regression coefficient (i=1, 2, 3,...,n)
X_i=independent variable represents concrete attributes m= no of training samples
ε=error term

This model is based on the mean square error that determines the distinction between the actual and computed values. This technique adjusts the coefficients of the independent variables using optimization methods and continues the procedure until the model is considered to be the best fit.

Extreme gradient boosting

It is called extreme gradient boosting where it has both linear and tree learning algorithms. It is fast as it does parallel computation on a single machine. It includes both regression and classification problems. XGB has high accuracy and but slow in implementation. The main concept of this type of boosting technique is, it takes the many weak learners and combines them into strong learners. Boosting technique can reduce the variance. The main advantage of using XGB or any other tree-based algorithm is its ability to model the non-linear interactions between the features [44].

All training sample is put into a decision tree (weighted sample 1) which gives a model denotes 2^{nd} weak classifier. The wrongly predicted data in the 2^{nd} classifier is sent into other decision trees (weighted sample 2) gives a model which denotes the 3^{rd} classifier. The process gets repeated until the weak learners combine to form strong learners. There will be multiple decision trees, only the wrong prediction is passed to the final model.

Description of Dataset and Preparation

Twelve concrete mixes as given in table 2 were produced by changing the w/c proportion and concrete substance. 7, 28, and 56 days are the curing ages. The input data for producing the model incorporates concrete substance (CC), water to cement ratio (W/C), super plasticizer (SP), fine aggregates (FA), recycled coarse aggregate (RCA), and water content (WC). The objective boundary is the exploratory compressive strength though, the output is assigned as Predicted compressive strength. Table 2 shows distinctive concrete substances with changing W/C. Table 3 shows the scope of information of input and output parameters.

Table 2: Different cement content with varying W/C

S.No	CC	W/C	SP	FA	RCA	WC	Age
1	300	0.35	1.5	604.58	1380.29	157.66	7, 28, 56
2	300	0.45	0	619.44	1290.32	186.49	7, 28, 56
3	300	0.55	0	631.37	1169	165	7, 28, 56
4	350	0.4	1.5	584.28	1273.66	189.68	7, 28, 56
5	350	0.5	0	591.74	1178.29	223.1	7, 28, 56
6	350	0.35	1.5	601.92	1374.33	174.93	7, 28, 56
7	400	0.48	0	557.73	1130.58	237.72	7, 28, 56
8	400	0.4	0	556.16	1212.29	207.29	7, 28, 56
9	400	0.3	1.5	550.69	1318.03	169.17	7, 28, 56
10	450	0.45	0.3	526.43	1096.34	246.25	7, 28, 56
11	450	0.35	0.3	523.57	1206.8	203.53	7, 28, 56
12	450	0.3	1.3	528	1263.71	182.15	7, 28, 56

Table 3: Information of input and output parameters

S.No		Parameters	Minimum	Maximum
1	Input	CC(kg/m^3)	300	450
2		W/C	0.3	0.55
3		SP (%)	0	1.5
4		FA (kg/m^3)	523.57	631.37
5		RCA (kg/m^3)	1096.34	1380.29
6		Water content (kg/m^3)	157.66	246.25
7		AGE (days)	7	56
8	output	Compressive strength (N/mm^2)	20.54 MPa	53.33 MPa

Experimental Investigations

Compressive strength test

The CSC test was executed using a 150 mm cube for cube compression strength and 100*200mm cylinder for cylinder compressive strength as per ASTM C 39 [45] and cured adequately using potable water following IS 456–2000 [48]. The CSC was determined for 7, 28, and 56 days. A compression Testing Machine with a capacity of 3000 kn is used for testing the cubes. At a rate of 140 kg/cm^2/min, the loading was increased consistently and identified the minimum load that can be supported by the cubes. These cubes were cured for 7, 28, and 56 days.

Results and Discussions

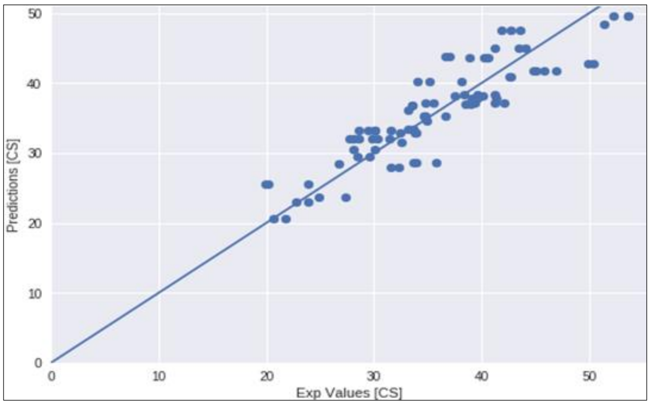
Data-driven models

In this study, 3 data-driven models namely MLR, XGB, ANN were established in python to produce an authentic model. In python programming, for linear regression, XGB should be defined for calling algorithms. This is done with the help of sklearn libraries. For conventional flat prediction model (MLR, ANN, XGB) splitting of data is done namely training, and testing. Training data includes 70% of the dataset (i.e), 202 patterns and testing data includes 30% of dataset (i.e), 86 patterns were divided.

MLR model

Program code: from sklearn. linear_model import linear regression
lr=linear regression()model (lr, train_X, train_Y, test_X,test_Y,"coef")

Figure 2 shows the contrasting graph between experimental values and predicted values of the MLR model where the values of Coefficient of determination R^2, RMSE is achieved.



RMSE: 3.3967667668714046
R^2 value: 0.8951774169812113

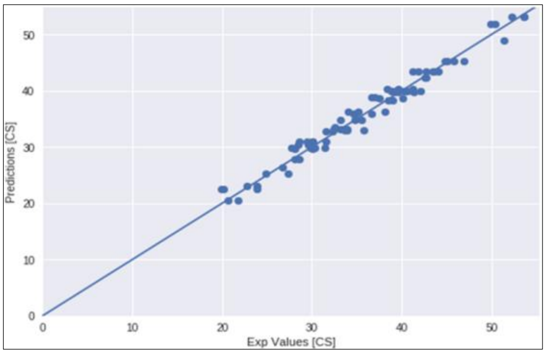
Fig 2: Relationship between predicted and experimental values in MLR model

XGB model

Algorithm for XG Boosting is taken from XG Boost. Sklearn library

Program code: Import xgboost as xgb from XG Boost. Sklearn import XGB Regressor
XGR =XGB Regressor () Model (xgr, train_X, train_Y, test_X, test_Y,"feat")

Figure 3 shows the contrasting graph between experimental values and predicted values of the XGB Regressor model where the values of Coefficient of determination R^2, RMSE is achieved.



RMSE: 1.238004117891868
R^2 value: 0.9867174534765205

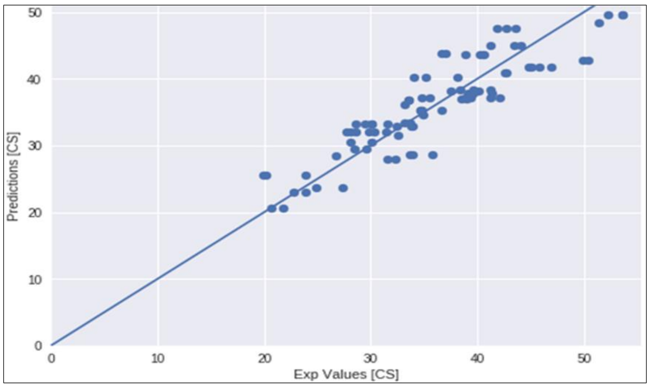
Fig 3: Relationship between predicted and experimental values in XG Boost Algorithm model

Artificial neural network

The total database in the present study was 288 cases, considering six inputs and one output. These data are divided into 70% for the training step and 30% for the testing step. The model should be built by architecture. The architecture of the ANN model was specified using the tensor flow library algorithm. They are:

1. Neurons in 1st layer: 06
2. No. of hidden layer: 02
3. Neurons in hidden layer: 256 neurons in 1st hidden layer and 128 neurons in 2nd hidden layer
4. No. of output: 01

Tensor flow is an open-source library for performing ANN operations. An algorithm in Tensor flow is used to develop the model. It was found that by tuning the hidden layer further, the R^2 value decreased. At 3000 epoch the model was found to be better in case R^2 and RMSE. Figure 4 shows the contrasting graph between experimental values and predicted values of the ANN model where the values of Coefficient of determination R^2, RMSE is achieved. Also, the studies [1, 2, 4, 7, 8, 11] inferred similar effects where the rate of prediction in ANN is greater than in any other regression analysis. Table 4 shows the Comparison of Correlation and statistical coefficients.



RMSE: 1.753584512246553
R^2 value: 0.9231674007255549

Fig 4: Relationship between predicted and experimental values in ANN model

Table 4: Comparison of Correlation and statistical coefficients

Model	RMSE	R^2
MLR	3.3967	0.8951
XGB	1.2380	0.9867
ANN	1.7535	0.9231

For the prediction of compressive strength of RAC mixes, the statistical approach of XGB was found to be 0.98 which is 6.4% greater than ANN and 9.3% greater than the MLR model. RMSE of XGB was found to be least in contrast with the other models, which states the accuracy of XG Boost. The same effect has been seen in the study [46] where XGB performs better than other models.

Experimental Results

Compressive strength

Cube compressive strength for RAC mixes observed at various testing ages has been done. Maximum CSC was observed for the cement content 400 kg/m^3 with w/c 0.3 and 1.5% of sp dosage. 56 d cube compressive strength ranges from 34.72MPa to 53.33 mpa. 28d strength ranges from 28.25MPa to 51.41MPa. 7d strength ranged from 18.15MPa to 40.16 MPa. The decrease was potential because of the followed mortar in RA, which influences the permeable ITZ thus turns into the most vulnerable point in RAC [47, 23]. Figures 5-8 shows the relationship between different cement content with varying w/c. Also, for each cement content for various curing ages, the equation to predict the compressive strength of concrete has been obtained. 56d of statistical approach ranges from 0.98 to 0.84. 28d of statistical approach ranges from 0.84 to 0.78. 7d of statistical approach ranges from 0.97 to 0.85. Correlations among the compressive strength of RAC mixes were established along with a good correlation coefficient range of around 0.98 to 0.85. Table 5 shows the interrelation between the cement content and different ages of curing.

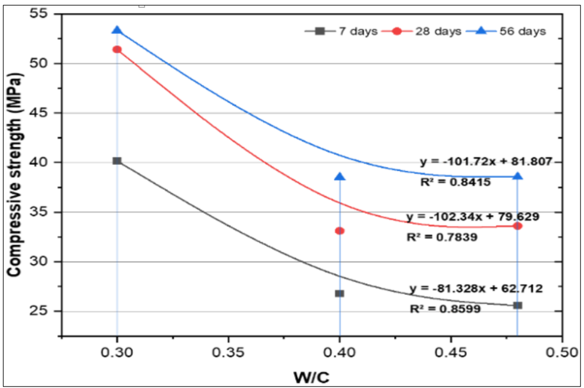


Fig 5: Interrelation between w/c and compressive strength for cement content 300kg/m^3

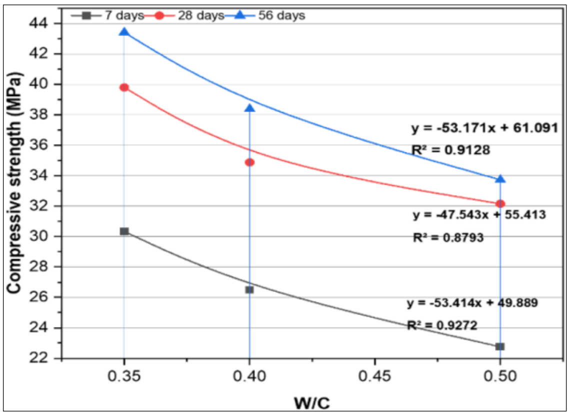


Fig 6: Interrelation between w/c and compressive strength for cement content 350kg/m^3

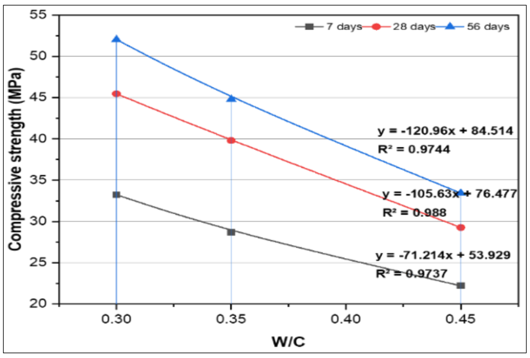


Fig 7: Interrelation between w/c and compressive strength for cement content 400kg/m^3

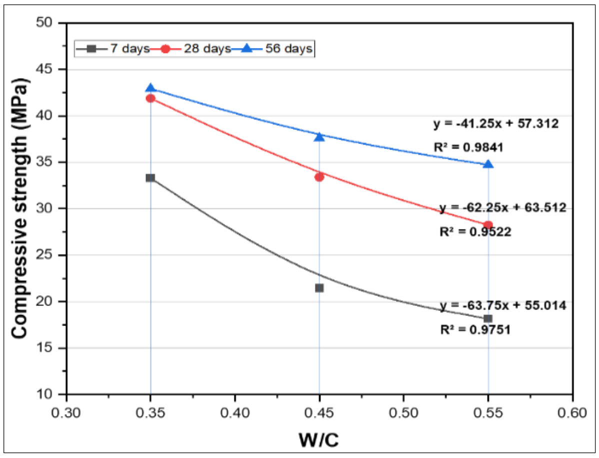


Fig 8: Interrelation between w/c and compressive strength for cement content 450kg/m^3

Table 5: Relationship between the cement content and different ages of curing

Cement content (Kg/m^3)	Age	R^2	Equation
300	7d	0.8599	Y= -81.328x +62.712
	28d	0.7839	Y= -102.34x +79.629
	56d	0.8415	Y= -101.72x +81.807
350	7d	0.9272	Y= -53.414x +49.889
	28d	0.8793	Y= -47.54x +55.413
	56d	0.9128	Y= -53.171x +61.091
400	7d	0.9737	Y= -71.214x +53.929
	28d	0.988	Y= -105.63x +76.477
	56d	0.9744	Y= -120.96x +84.514
450	7d	0.9751	Y= -63.75x +55.014
	28d	0.9522	Y= -62.25x +63.512
	56d	0.9841	Y= -41.25x +57.312

Density

Hardened density for various ages of RAC mixes has been inferred. The maximum density was recorded within the range of 2409 kg/m^3 to 2576 kg/m^3 for 56 d strength. For 28d the density was found between 2393 kg/m^3 to 2500 kg/m^3, 7d density was found within the range of 2572 kg/m^3 to 2413 kg/m^3.

Conclusions

RCA was found to be finer than NA, the fineness modulus of RCA is 6.77 % greater than that of NA. The average specific gravity of RCA was discovered to be 2.55 which is lesser than NA by 6.1%. The average water absorption (%) of RCA was discovered to be 1.95 though for NA it was found to be 0.36, which is roughly 5.41 times of NA.

The relationship between the w/c and compressive strength of concrete for various cement content for concerning curing ages has been derived.

Cement content of 400kg/m3 was found to have optimum results in terms of strength and R^2 value for 28 days followed by other cement content.

Compressive strength of concrete for cement content for 56d of 400kg/m^3 was found to have 53.33 MPa which is 19%, 18.5% and 2.5% greater than 300kg/m^3, 350kg/m^3 and 450kg/m^3 respectively. For 28d 400kg/m^3 was found to have 51.41MPa which is 18.5%,22.5% and 11.6% greater than 300kg/m^3, 350kg/m^{3}and 450kg/m^3 respectively.

For 7d 400kg/m^3 was found to have 40.16MPa which is 17.1%, 24.5% and 17.2% greater than 300kg/m^3, 350kg/m^3 and 450kg/m^3 respectively.

Cement content of 450kg/m^{3}and w/c of 0.3 with sp of 1.5% was found to have maximum density of 2576kg/m^3 on 56 days which is 3.9%, 5% and 5.2% greater than 300kg/m^3, 350kg/m^3 and 400kg/m^3 respectively.

Due to pores, cracks, and voids the strength of concrete the water absorption has been increased which decreased the compressive strength of concrete.

From the modeling techniques, for both accurate and easy work, XGB was found to have greater results with higher R^2 and least RMSE value followed by ANN and then by MLR. By receiving these foreseeing strategies, impressive expense and tedious lab tests have been saved [9, 11].

References

1. Ferhet Bingol A, Ahmet Totum, Rustem Gul. "Neural network analysis of compressive strength of light weight concrete after high temperature", Materials and Design,2013:52:258-264.
2. Ahmed M, Diab, Hafez E, Elyamany Adb Elmoaty M, Abd Elmoaty Ali H *et al*. "Prediction of concrete compressive strength due to long term sulfate attack using neural network", Alexandria Engineering journal,2014:53(3):627-642
3. Farzehossadat khademi, Sayed Mohammadmehdi Jamal, Neela Deshpande, Shreenivas Londe. "Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multi linear regression", International journal of sustainable built environment,2016:5(2):355-369
4. Jafar Sobhani, Meysam Najimi, Ali Reza Pourkhorshidi, Tayebh Parhizkar. "Prediction of the compressive strength of no slump concrete: A comparative study of regression, neural network and ANFIS models", construction and building materials,2010:24:709-718.
5. Jui-Sheng chou, Anh-Duc Pham. "Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength", Construction and building materials,2013:49:554-563
6. Jui-Sheng Chou, Chih-Fong Tsai. "Concrete compressive strength analysis using a combined classification and regression technique", Automation in construction,2012:24:52-60
7. Neela Deshpande, Shreenivas Londe, Sushma Kulkarni. "Modelling compressive strength of recycled coarse aggregate by artificial neural network, model tree and non-linear regression", International journal of sustainable built environment,2014:3(2):187-198
8. Chithra S, Senthil kumar SRR, Chinnaraju K, Alfin Ashmita F. "A comparative study on the compressive strength prediction models for HPC containing nano-silica and copper slag using regression analysis and artificial neural network", Construction and building materials,2016:114:528-535.
9. Seyyed Mohammad Mousavi, Pejman Aminian, Amir Hossein Gandomi, Amir Hossein Alavi, Hamed Bolandi. "A new predictive model for compressive strength of HPC using gene expression programming", Advances in engineering software,2012:45:105-114.
10. Atici U. "Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network", Expert system in applications,2011:38(8):9609-9618
11. Zhe yuan, Lin-Na Wang, Xu ji. "Prediction of concrete compressive strength: Research on hybrid models genetic based algorithms and ANFIS", Advances in engineering software,2014:67:156-163.
12. Evangelista L, de Brito J. Durability performance of concrete made with fine recycled concrete aggregates, Cem. Concr. Compos,2010:32(1):9-14
13. Zaharieva R, Buyle-Bodin F, Skoczylas F *et al*. Assessment of the surface permeation properties of recycled aggregate concrete, Cem. Concr. Compos,2003:25(2):223-232.
14. Sim J, Park C. Compressive strength and resistance to chloride ion penetration and carbonation of recycled aggregate concrete with varying amount of fly ash and fine recycled aggregate, Waste Manage,2011:31(11):2352-2360;.
15. Corinaldesi V, Moriconi G. Behaviour of cementitious mortars containing different kinds of recycled aggregate, Constr. Build. Mater,2009:23(1):289-294.
16. Lee ST. Influence of recycled fine aggregates on the resistance of mortars to magnesium sulfate attack, Waste Manage,2009:29(8):2385-2391
17. Corinaldesi V. Mechanical and elastic behaviour of concretes made of recycled-concrete coarse aggregates, Constr. Build. Mater,2010:24(9):1616-1620.
18. Belén GF, Fernando MA, Diego CL *et al*. Stress-strain relationship in axial compression for concrete using recycled saturated coarse aggregate, Constr. Build. Mater,2011:25(5):2335-2342.
19. González-Fonteboa B, Martínez-Abella F. Shear strength of recycled concrete beams, Constr. Build. Mater,2007:21(4):887-893.
20. Liu Q, Xiao JZ, Sun ZH. Experimental study on the failure mechanism of recycled concrete, Cem. Concr. Res,2011:41(10):1050-1057.
21. Fathifazl G, Razaqpur AG, Isgor OB *et al*. Creep and drying shrinkage characteristics of concrete produced with coarse recycled concrete aggregate, Cem. Concr. Compos,2011:33(10):1026-1037.
22. Etxeberria M, Vázquez E, Marí A *et al*. Influence of amount of recycled coarse aggregates and production process on properties of recycled aggregate concrete, Cem. Concr. Res,2007:37(5):735-742.
23. Poon CS, Shui ZH, Lam L. Effect of microstructure of ITZ on compressive strength of concrete prepared with recycled aggregates, Constr. Build. Mater,2004:18(6):461-468.
24. Taofeek D, Akinosho, Lukumon O, Oyedele Muhammad Bilal, Anuoluwapo O, Ajayi *et al*. Deep learning in the construction industry: A review of the present status and future innovations. Journal of Building Engineering, 2020, (32). https://doi.org/10.1016/j.jobe.2020.101827
25. Vivian WY, Wang K, Tam CM. Assessing relationships among properties of demolished concrete recycled aggregate and recycled aggregate concrete using regression analysis. J. Hazard. Mater,2008:152:703-714. https://doi.org/10.1016/j.jhazmat.2007.07.061
26. Deepa C, Sathiya Kumari K, Pream Sudha K. Prediction of the compressive strength of high-performance concrete mix using tree-based modeling. Int. J. Comput. Appl,2010:6(5):18-24.
27. Neter J, Kutner MH, Nachtsheim CJ, Wasserman W. Applied Linear Statistical Models. Fourth ed. IRWIN, 1996.
28. Hong-Guang N, Ji-Zong W. Prediction of compressive

strength of concrete by neural networks. Cem Concr Res,2000:30(8):1245-50. https://doi.org/10.1016/S0008-8846(00)00345-8
29. Oztas A, Pala M, Ozbay E, Kanca E, Caglar N, Bhatti MA. Predicting the compressive strength and slump of high strength concrete using neural network. Constr Build Mater,2006:20(9):769-75. https://doi.org/10.1016/j.conbuildmat.2005.01.054
30. Bilim C, Atis CD, Tanyildizi H, Karahan O. Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network. Adv Eng Soft,2009:40(5):334-40. https://doi.org/10.1016/j.advengsoft.2008.05.005
31. Ramezanianpour AA, Sobhani M, Sobhani. J. Application of a network-based neuro-fuzzy system for prediction of the strength of high strength concrete. Amirkabir J Sci Technol,2004:15(59):78-93.
32. Revathi Purushothaman, Ramesh Ruthirapathy Amirthavalli, Lavanya Karan. Influence of Treatment Methods on the Strength and Performance Characteristics of Recycled Aggregate Concrete. J. Mater. Civ. Eng,2015:27(5):10. 1061/(ASCE)MT.1943-5533.0001128
33. Özcan F, Atis CD, Karahan O, Uncuog˘lu E, Tanyildiz H. Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete. Adv Eng Soft,2009:40(9):856-63. https://doi.org/10.1016/j.advengsoft.2009.01.005
34. Yilmaz I, Yuksek G. Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. Int J Rock Mech Mining Sci,2009:46(4):803-10.
35. Waszczyszyn Z, Słon´ski M. some problems of artificial neural networks design In: Waszczyszyn Z, editor. Advances of soft computing in engineering. CISM lectures and notes, New York,2010:512:237-316
36. Yu Li, Jin Gou, Zongwen Fan. Particle swarm optimization-based extreme gradient boosting for concrete strength prediction. IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC 2019), ©2019 IEEE, 2019:978(1)7281-1907-6/19. https://doi.org/10.1109/IAEAC47372.2019.8997825
37. Sivakumar N. “Experimental Studies on High Strength Concrete by using Recycled Coarse Aggregate”. Journal of materials in civil engineering, 2014, 30(8). https://doi.org/10.1061/(ASCE)MT.1943-5533.0002398
38. Ahmed SFU. “Properties of Concrete Containing Construction and Demolition Wastes and Fly Ash”. Journal of materials in civil engineering, 2013, 25(12). https://doi.org/10.1061/(ASCE)MT.1943-5533.0000763
39. IS 383. Indian Standard Specification for Coarse and Fine Aggregates – Specification (Third Revision
40. IS 2386 (Part 1). Methods of Test for Aggregates for Concrete, Bureau of Indian Standards, India, 2002.
41. IS 2386 (Part 3): Methods of test for Aggregates for Concrete: Determination of Specific Gravity. Reaffirmed- Dec 2016, 1963.
42. Rakesh Kumar. “Influence of recycled coarse aggregate derived from construction and demolition waste (CDW) on abrasion resistance of pavement concrete” Construction and Building Materials,2017:142:248-255. DOI:10.1016/j.conbuildmat.2017.03.077
43. Jian Yang, Qiang Du, Bao YW. “Concrete With Recycled Concrete Aggregate and Crushed Clay Bricks April”, Construction and Building Materials,2011:25(4):1935-1945. DOI:10.1016/j.conbuildmat.2010.11.063
44. Caruana R, Niculescu-Mizil A. An empirical comparison of supervised learning algorithms. In: Proceedings of the 23 rd international conference on Machine learning. ACM, 2006, 161-168. https://doi.org/10.1145/1143844.1143865
45. ASTM C39, Standard Test Method for Compressive Strength of Cylindrical Concrete Specimens, ASTM International, West Conshohocken, PA, 2018
46. Jin Duan, Panagiotis G. Asteris, Hoang Nguyen, Xuan-Nam Bui, Hossein Moayedi. A novel artificial intelligence technique to predict the compressive strength of recycled aggregate concrete using ICA-XGBoost model. Engineering with Computers, 2020. https://doi.org/10.1007/s00366-020-01003-0
47. Etxeberria M, Vázquez E, Marí A *et al*. Influence of amount of recycled coarse aggregates and production process on properties of recycled aggregate concrete, Cem. Concr. Res,2007:37(5):735-742.
48. IS 456. Plain and reinforced concrete- code of practice, Bureau of Indian Standards, New Delhi, 2000.