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Compressive Strength Prediction via Gene Expression Programming (GEP) and Artificial Neural Network (ANN) for Concrete Containing RCA

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Abstract: To minimize the environmental risks and for sustainable development, the utilization of recycled aggregate (RA) is gaining popularity all over the world. The use of recycled coarse aggregate (RCA) in concrete is an effective way to minimize environmental pollution. RCA does not gain more attraction because of the availability of adhered mortar on its surface, which poses a harmful effect on the properties of concrete. However, a suitable mix design for RCA enables it to reach the targeted strength and be applicable for a wide range of construction projects. The targeted strength achievement from the proposed mix design at a laboratory is also a time-consuming task, which may cause a delay in the construction work. To overcome this flaw, the application of supervised machine learning (ML) algorithms, gene expression programming (GEP), and artificial neural network (ANN) was employed in this study to predict the compressive strength of RCA-based concrete. The linear coefficient correlation (R^2), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) were evaluated to investigate the performance of the models. The k-fold cross-validation method was also adopted for the confirmation of the model's performance. In comparison, the GEP model was more effective in terms of prediction by giving a higher correlation (R^2) value of 0.95 as compared to ANN, which gave a value of R^2 equal to 0.92. In addition, a sensitivity analysis was conducted to know about the contribution level of each parameter used to run the models. Moreover, the increment in data points and the use of other supervised ML approaches like boosting, gradient boosting, and bagging to forecast the compressive strength, would give a better response.

Keywords: recycled coarse aggregate; cement; concrete; gene expression programming; artificial neural network; machine learning

1. Introduction

The utilization trend of aggregate obtained from natural resources increases sharply from the increased manufacturing and usage of concrete in the construction sectors [1,2]. The largest consumers of the natural aggregates are construction industries [3]. A total of 15 billion tons of concrete material is produced worldwide, which equates to about two tons of concrete per resident per annum [4]. To reduce this flaw and manage this demand, the origin of good quality natural aggregates is significantly reducing worldwide [5]. The approximate amount of aggregate used in the European Union countries has reached two billion each year. The activities related to construction demand a high number of natural materials to produce cement and aggregate. However, the construction sectors are an enormous consumer of natural resources, producing huge amounts of waste [6]. The application of raw materials in the construction industry is the key factor that causes environmental risks and pollution to earth [7]. The usage of raw materials has also led to the depletion of minerals as well as natural resources [8]. Resources including cement, fine aggregate, and coarse aggregate will be at a deprived status because these resources cannot manage the increasing demand in the construction industry [9]. Furthermore, sustainable waste management is one of the most crucial matters experienced by the world. Therefore, to minimize the environmental impact and energy consistency of concrete applied to construction work, the utilization of demolition and construction wastes can be favorable for a sustainable engineering approach for the mixed design of concrete. The use of recycled coarse aggregate (RCA) can also be a significant and positive aspect to achieve sustainable construction and reduce environmental risks [10].

The main difference between the natural aggregate and recycled coarse aggregate (RCA) is a certain amount of sticky mortar at the surface of RCA [11]. The properties of RCA vary with certain percentages from the natural aggregate. RCA is generally a porous material, having low saturated surface dry density and bulk density, 2310–2620 kg/m^3 and 1290–1470 kg/m^3, respectively [12]. The porosity of RCA is due to a high content of adhered mortar on its surface, which also reduces its resistance against the chemical and mechanical effects. In comparison, RCA also shows a high value of water absorption (4% to 9%) as opposed to natural aggregate (1% to 2%) [13]. The porosity and water absorption are normally increased in RCA just because of the amount of adhered mortar [14,15]. The effect on density and absorption capacity is also affected by the adhered mortar. These parameters affect the fresh properties of concrete and reduce the strength properties of concrete. The proper mix design for RCA has assured the acceptable properties of concrete which can be used in several construction projects. The properties of concrete material can also be improved by using other waste materials like silica fume, fly ash, and natural and artificial fibers [16–19].

Several studies were presented regarding the application of recycled aggregate (RA) in concrete at certain percentages [20,21]. Several properties of concrete were investigated upon the inclusion of RA in concrete, including the fresh properties and mechanical properties of RA-based concrete [22–24]. The different qualities of RA were employed in concrete for maintaining or increasing the strength properties of concrete [25–28]. They also showed that the targeted strength was achieved even at an 80% replacement of coarse aggregate with RCA. Khaldoun et al. [23] worked on the effect of mechanical properties of concrete containing RCA. The compressive strength of the specimens at different ages was calculated to analyze the behavior of concrete. Muzaffer et al. [29] described the mechanical and physical properties of RCA concrete GGBFS, in which they concluded that the split tensile strength was improved when tested at various ages of specimens. Etxeberria et al. [30] showed the influence of RCA and the production process on the properties of recycled aggregate-based concrete. They prepared concrete with 0%, 25%, 50%, and 100% recycled aggregate to investigate the properties. Sumayia et al. reported the mechanical properties of three generations of 100% repetition of RCA. They reported the idea that the repeated RA experienced marginally lower compressive strength than the normal concrete.

Supervised machine learning (ML) techniques are extensively used in the fields of artificial inelegance (AI) and computer science and have a positive reflection in engineering. However, it has gained rapid promotion in the field of civil engineering, especially when it comes to predicting the strength properties of concrete. The supervised ML approaches can be employed, which can predict the outcomes at high accuracy. Ayaz et al. [31] predicted the compressive strength of fly ash-based concrete with individual and ensemble ML approaches. Miao et al. [32] used MLR, SVM, and ANN to foretell the bond strength between the FRPs and concrete, in which they compared the accuracy level of the predictions from the employed techniques. Khoa et al. [33] used ML algorithms to forecast the compressive strength of greenfly ash-based geopolymer concrete. Marjana et al. used different ML techniques for predicting the compressive strength of concrete. The predicted accuracy and the error distribution were analyzed in the study. Ayaz et al. [34] used artificial neural network (ANN), gene expression programming (GEP), and decision tree (DT) techniques to forecast the surface chloride concentration in concrete containing waste material. They indicated that the GEP was a more effective technique for prediction than other employed algorithms. This research also focuses on the application of supervised ML approaches to forecast the compressive strength of recycled coarse aggregate-based concrete. The ANN and GEP algorithms have been investigated to predict the compressive strength of concrete containing recycled aggregate. The various statistical checks, k-fold cross-validation method, and error distribution are included to confirm the model performance. The focus of this study is on the application of supervised machine learning algorithms (gene expression programming and artificial neural network) to predict the compressive strength of concrete containing recycled coarse aggregate (RCA) of 344 data points. The aim of this research also describes the performance of gene expression programming (GEP) and an artificial neural network (ANN) in terms of the correlation coefficient (R^2) value. The statistical checks, evaluation of errors (MAE, MSE, and RMSR), k-fold cross-validation, and sensitivity analysis were also involved to evaluate the performance of both GEP and ANN models. This study can be useful for researchers in the field of civil engineering to foretell the strength properties without consuming more time on practical work in the laboratory.

2. Data Description

Supervised machine learning algorithms require various input variables to give the output predicted variable. The data used in this study to forecast the compressive strength of recycled coarse aggregate-based concrete were taken from previously published literature and can be seen in Appendix A. A total of nine parameters including water, cement, sand, natural coarse aggregate, recycled coarse aggregate (RCA), superplasticizers, size of RCA, the density of RCA, and water absorption of RCA were taken as input for running the models, and one variable, compressive strength, was taken as an outcome for the models. Several input parameters and the total number of data points greatly influence the model's outcome. A total of 344 data points (mixes) for the prediction of RCA-based concrete were used in the study. Anaconda software was introduced to run the model for ANN using python coding, while the GEP model was run on the GEP software. The relative frequency distribution of each parameter used for the mixes can be seen in Figure 1. The descriptive statistical analysis for all the parameters is listed in Table 1. The flowchart of the research approach can be seen in Figure 2.

Table 1. Descriptive analysis of the input parameters.

Parameter's Descriptions	Water	Cement	*FA	*NCA	*RCA	*SP	*SRCA	*DRCA	*WRCA
Mean	184.62	386.86	681.89	398.07	650.74	1.32	19.76	2231.06	4.80
Standard Error	1.39	4.43	11.07	19.99	20.37	0.11	0.22	31.32	0.12
Median	180.00	380.00	698.00	471.00	552.00	0.00	20.00	2362.50	4.90
Mode	220.00	380.00	693.00	0.00	138.00	0.00	20.00	2320.00	5.30
Standard Deviation	25.84	82.16	205.28	370.71	377.73	2.05	4.02	580.95	2.26
Sample Variance	667.47	6750.28	42,141.11	137,424.94	142,682.56	4.21	16.16	337,504.80	5.12
Kurtosis	−0.13	−0.19	4.17	−1.13	−0.32	0.61	2.23	10.55	1.07
Skewness	−0.01	0.43	−1.82	0.30	0.51	1.36	0.08	−3.45	0.06
Range	153.40	442.00	1010.00	1448.25	1726.00	7.80	22.00	2661.00	10.90
Minimum	117.60	158.00	0.00	0.00	52.00	0.00	10.00	0.00	0.00
Maximum	271.00	600.00	1010.00	1448.25	1778.00	7.80	32.00	2661.00	10.90
Sum	63,510.69	133,081.00	234,568.66	136,937.02	223,853.20	455.50	6796.00	767,484.00	1652.80
Count	344.00	344.00	344.00	344.00	344.00	344.00	344.00	344.00	344.00

*FA = Fine aggregate, *NCA = Natural coarse aggregate, *SP = Superplasticizer, *SRCA = Maximum size of recycled coarse aggregate, *DRCA = Density of recycled coarse aggregate, *WRCA = Water absorption of recycled-coarse aggregate.

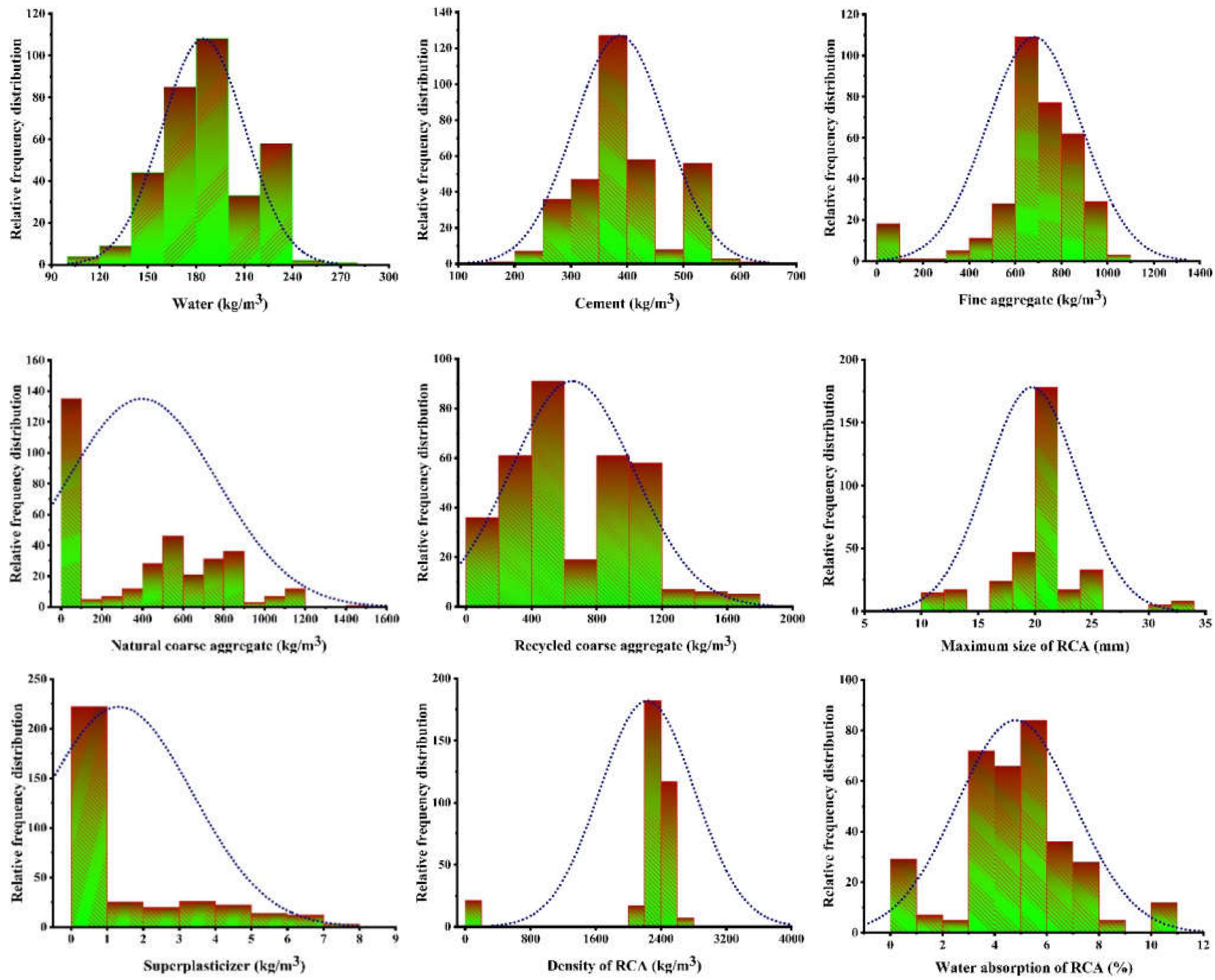

Figure 1. Histograms indicating the relative frequency distribution of the input parameters.

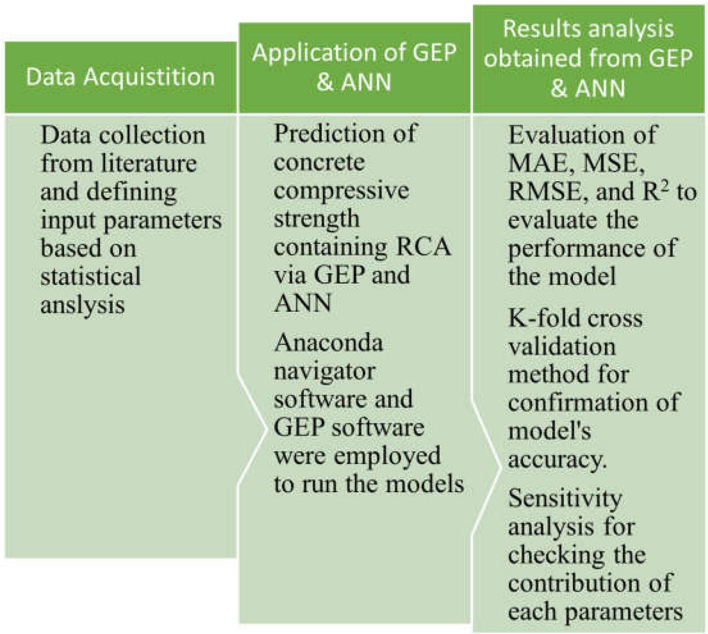

Figure 2. Flowchart of the research approach.

3. Methodology

Two algorithms (GEP and ANN) were introduced in the study to predict the compressive strength of RAC. Spyder 4.1.1 was selected in the Anaconda navigator to run the model for the artificial neural network (ANN) using python coding. However, the GEP, which is the computer-based software, was adopted for modeling to give a predicted compressive result for the concrete containing recycled coarse aggregate. The GEP and ANN used nine parameters as input and one parameter (compressive strength) as the output during the modeling. The predicted outcome from both models presented the correlation coefficient (R^2) value, which is an indication of the accuracy level. The R^2 value normally ranges from 0–10, and a higher R^2 value indicates a high accuracy between the actual and predicted result. Gene expression programming is from the family of evolutionary algorithms and is generally associated with genetic programming. GEP being from the evolutionary algorithms, can design computer programs and models. Computer programming is considered as a composite tree-like structure that learns and alters by substituting their shapes, compositions, and sizes similar to living organisms. The GEP computer program is included in simple linear chromosomes of fixed length. GEP consists of five components: terminal set, function set, controlee variable, fitness function, and terminate condition. Ferreira presents GEP in 2006, which is a modified form of genetic programming (GP) and depends on the population evolutionary theorem. An exceptional tempering in GEP was that the single gene must be transferred to another generation and has no need to reproduce and mutate the complete structure since every alteration takes place in a linear and simple structure. Each gene in GEP contains a fixed-length variable having terminal sets and arithmetic operations as a set of functions. GEP makes it possible to learn the complex data in the form of input and gives the resulting output in a simple and easy manner. An artificial neural network (ANN) is generally a segment of a computing system that is designed in such a way that it can simulate just like the human brain and inspect and execute a set of information. ANN is the foundation of artificial intelligence (AI), which can resolve problems that would seem difficult or impossible for a human. It is also comprised of self-learning potential, which permits them to generate better results. ANN is designed like a human brain having neuron nodes interrelated just like a web. The brain consists of hundreds of billions of cells known as neurons. Every neuron is prepared with a cell body that is accountable for executing the information by taking information towards and away from the brain. The application of ANN is reflected in every industry and field to predict required outcomes.

4. Results and Their Analyses

4.1. Statistical Analysis

The statistical analysis representation between the actual and predicted outcomes (for compressive strength of RCA-based concrete) from the GEP and ANN models along their error distribution can be seen in Figure 3. The GEP gives high accuracy and less variance between the actual and predicted output. The coefficient correlation (R^2) value equals 0.95 and is an indication of its high performance towards the prediction of the result, as shown in Figure 3a. The scattering of errors for the GEP model is also illustrated in Figure 3b. The error distribution in Figure 3b represents that the maximum, minimum, and average values of the training set were 22.37 MPa, 0.00 MPa, and 1.84 MPa, respectively. However, 21.73% of the error data lies below 1 MPa, and 22.96% of the data represented the errors between 2 MPa and 5 MPa. However, only 6.97% of the data lies above the 5 MPa.

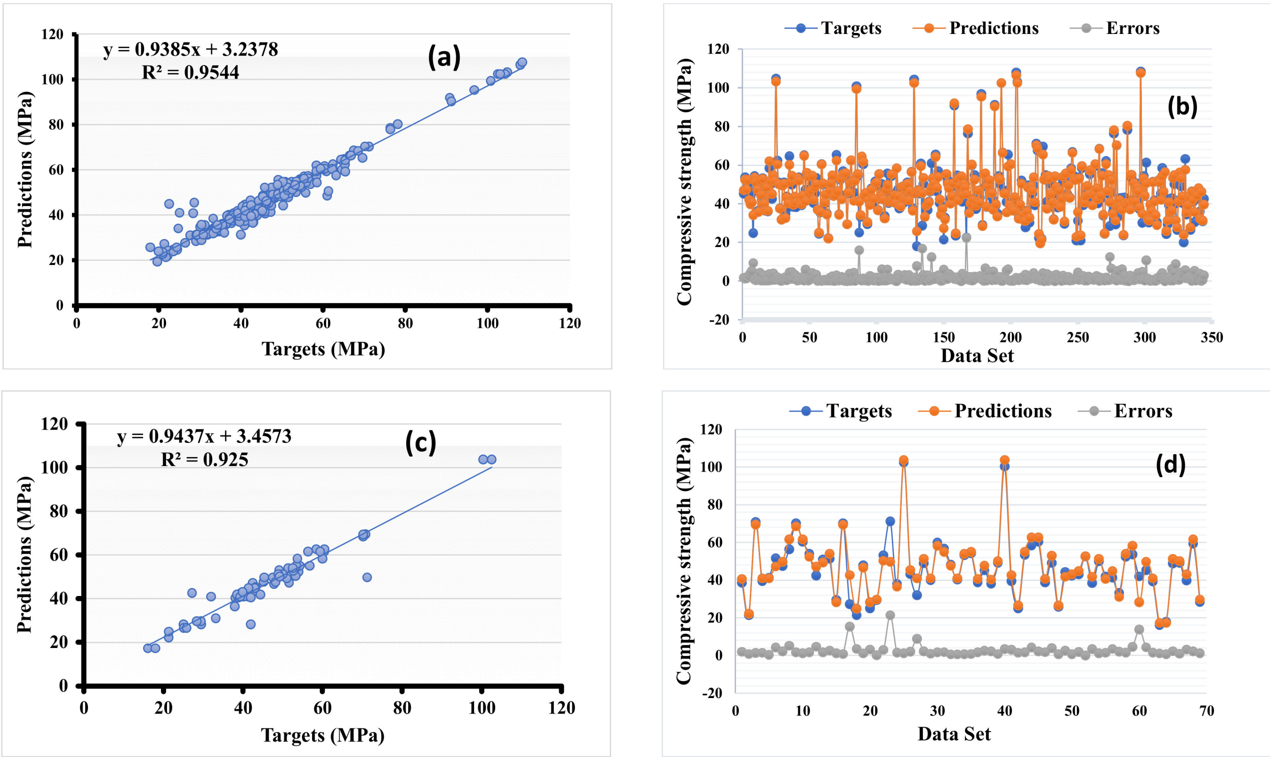

Figure 3. Numerical analysis results illustrating the relationship among the actual and predicted outcomes and reflection of errors distribution of the models. ANN (**a**,**b**); GEP (**c**,**d**).

The result of the ANN model is also in the acceptable range with less variance as opposed to the GEP model's result. The relationship between the actual and predicted result from the ANN model with the value of R^2 equal to 0.92 can be seen in Figure 3c. The distribution of the errors for the ANN model can be seen in Figure 3d. Figure 3d gives the information of the training set of the ANN model, indicating maximum and minimum values of 21.44 MPa and 0.1 MPa, respectively, while giving an average value of 2.72 MPa. In addition, 21.73% of error data lies below 1 MPa, and 36.23% of data lies between 2 MPa and 5 MPa. However, only 7.24% of the error data indicated above the 5 MPa.

4.2. K-Fold Cross-Validation

The authenticity of the model's execution was analyzed through the k-fold cross-validation method. To examine the model's validity, the k-fold cross-validation process is normally adopted, in which the required data has been arranged randomly and divided into ten groups. The nine groups need to be allocated for training and the remaining one for the model's validation. The procedure also needs repetition (ten times) to have an average output. This detailed process of the k-fold cross-validation results in the high accuracy of the models. In addition, the statistical checks in the form of the error's (MSE, MAE, and RMSE) evaluation have also been carried out, as illustrated in Table 2. The response of the models towards the prediction was also checked through the statistical analysis, illustrated in the form of the equations stated below. (Equations (1)–(5))

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (ex_i - mo_i)^2}{n}} \tag{1}$$

$$MAE = \frac{\sum_{i=1}^{n} |ex_i - mo_i|}{n} \tag{2}$$

$$RSE = \frac{\sum_{i=1}^{n} (mo_i - ex_i)^2}{\sum_{i=1}^{n} (\overline{ex} - ex_i)^2} \tag{3}$$

$$RRMSE = \frac{1}{e}\sqrt{\frac{\sum_{i=1}^{n}(ex_i - mo_i)^2}{n}} \tag{4}$$

$$R = \frac{\sum_{i=1}^{n}(ex_i - \overline{ex}_i)(mo_i - \overline{mo}_i)}{\sqrt{\sum_{i=1}^{n}(ex_i - \overline{ex}_i)^2 \sum_{i=1}^{n}(mo_i - \overline{mo}_i)^2}} \tag{5}$$

where,

ex_i = experimental value,
mo_i = predicted value,
$\overline{ex}_i$ = mean experimental value,
$\overline{mo}_i$ = mean predicted value obtained by the model,
n = number of samples.

The resulting evaluation of the k-fold cross-validation comprised of four parameters, including the coefficient correlation (R^2), mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE), and their distribution can be seen in Figure 4. The lesser error of the GEP model with a high value of R^2 indicates the better performer for prediction of outcome. The maximum, minimum, and average values of R^2 for the GEP model were equal to 0.77, 0.00, and 0.49, respectively, as shown in Figure 4a. Similarly, the same values of R^2 for the ANN model were 2.05, 0.00, and 0.68, as depicted in Figure 4b. However, the maximum values of the MAE, MSE, and RMSE for the GEP model were 14.37 MPa, 14.11 MPa, and 3.76 MPa, respectively, as illustrated in Figure 4a, while the validation result for the ANN model gave maximum values of MAE, MSE, and RMSE as 16.80 MPa, 20.89 MPa, and 4.57 MPa, respectively, as shown in the Figure 4b. The minimum values of the errors (MAE, MSE, and RMSE) for the GEP model were 6.21 MPa, 8.17 MPa, and 2.86 MPa, as reflected in Figure 4a, while for ANN, these values were 5.86 MPa, 4.96 MPa, and 2.23 MPa, as depicted in Figure 4b. Additionally, the validation result for the GEP and ANN models and the statistical checks for both, employing the supervised machine learning algorithms, are illustrated in Tables 2 and 3, respectively.

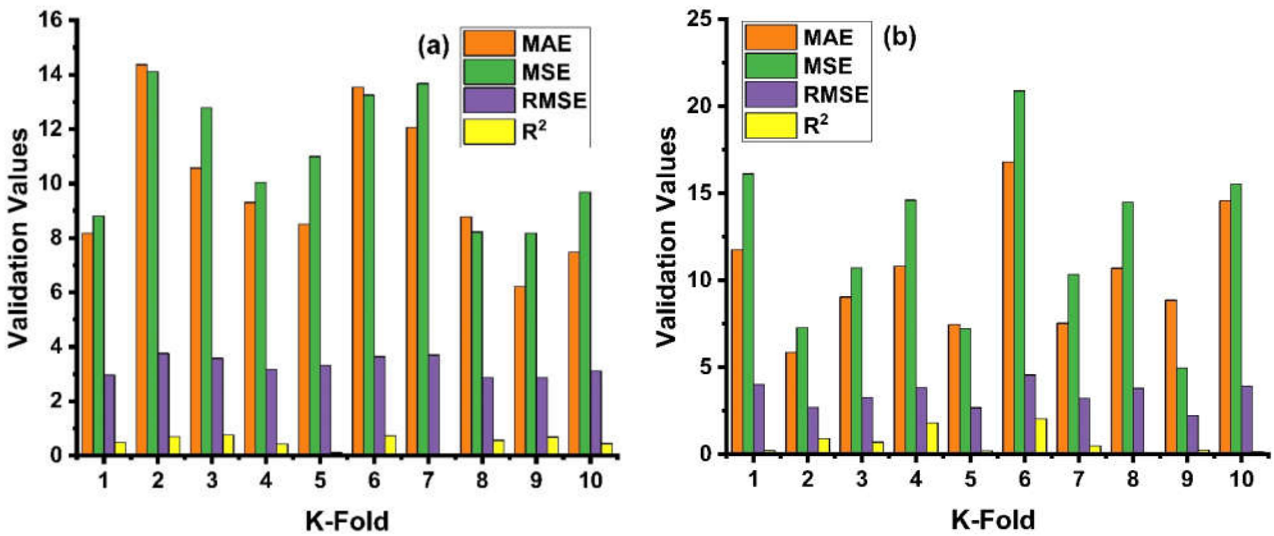

Figure 4. Statistical representation for the k-fold cross-validation process. GEP (**a**); ANN (**b**).

Table 2. Statistical checks of the GEP and ANN models.

Machine Learning Algorithms	MAE	MSE	RMSE
Gene Expression Programming (GEP)	1.84	9.3	3.05
Artificial Neural Network (ANN)	2.73	19	4.36

Table 3. Analysis of the k-fold cross-validation of ANN and GEP models.

ANN					GEP				
K-Fold	MAE	MSE	RMSE	R^2	K-Fold	MAE	MSE	RMSE	R^2
1	11.77	16.13	4.02	0.22	1	8.17	8.81	2.97	0.49
2	5.86	7.28	2.70	0.91	2	14.37	14.11	3.76	0.70
3	9.04	10.72	3.27	0.70	3	10.57	12.79	3.58	0.77
4	10.81	14.60	3.82	1.82	4	9.31	10.04	3.17	0.43
5	7.46	7.23	2.69	0.20	5	8.51	10.99	3.32	0.12
6	16.80	20.89	4.57	2.05	6	13.55	13.25	3.64	0.74
7	7.54	10.34	3.22	0.49	7	12.07	13.67	3.70	0.00
8	10.70	14.50	3.81	0.00	8	8.77	8.22	2.87	0.56
9	8.86	4.96	2.23	0.26	9	6.21	8.17	2.86	0.69
10	14.58	15.53	3.94	0.16	10	7.49	9.68	3.11	0.44

5. Sensitivity Analysis

This analysis refers to the effect of parameters on predicting the compressive strength of concrete containing recycled coarse aggregate, as depicted in Figure 5. The input parameters have a significant effect on forecasting the outcomes. The figure illustrates that the highest contributor was the recycled coarse aggregate (RCA) at 41.1%, while the other two main contributors were natural coarse aggregate (NCA) and water at 25% and 20%, respectively. However, the contribution of the other variables was less, and for cement, it showed a 3.8% contribution, fine aggregate 2.3%, superplasticizers 2.6%, the size of coarse aggregate 1.9%, the density of RCA 2%, and water absorption showed 1.3% contribution towards the prediction of the compressive strength of RCA-based concrete. The following equation was used to calculate the contribution of each variable towards the model's output.

$$N_i = f_{max}(x_i) - f_{min}(x_i) \tag{6}$$

$$S_i = \frac{N_i}{\sum_{j-i}^{n} N_j} \tag{7}$$

where, $f_{max}(x_i)$ and $f_{min}(x_i)$ are the maximum and minimum of the estimated output over the ith output.

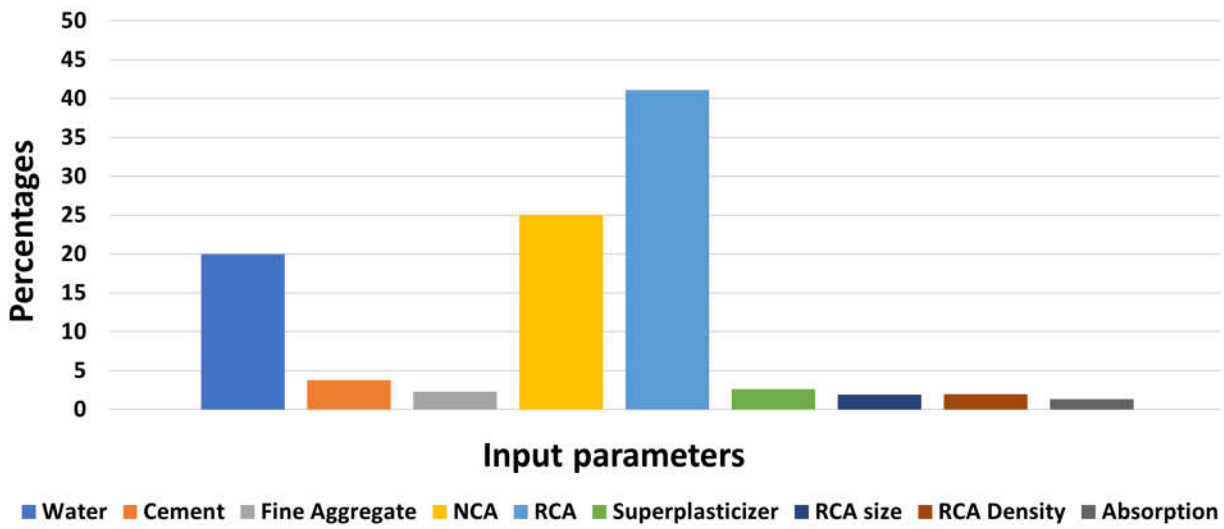

Figure 5. Sensitivity analysis indicates the contribution of parameters towards the prediction.

6. Discussion

This research describes the application of supervised machine learning (ML) techniques to foretell the strength property (compressive strength) of recycled coarse aggregate-based concrete. The use of recycled aggregates in concrete is to produce effective material and sustainable construction works. The ML approaches used in this study were gene expression programming (GEP) and an artificial neural network (ANN). The predictive performance of both algorithms was compared to evaluate the better predictor. The GEP model's outcome was more accurate by indicating the coefficient correlation (R^2) value equal to 0.95 as opposed to the ANN model's outcome which gave an R^2 value equal to 0.92. The performance of both models was also confirmed from the statistical checks and k-fold cross-validation method. The lesser values of the errors indicate the high performance of the employed model. Moreover, the sensitivity analysis was also carried out to know about the contribution of each parameter towards the prediction of the compressive strength of concrete containing recycled coarse aggregate. The performance of the models can be affected by the input parameters used to run the model and the number of data points. The contribution level from the sensitivity analysis of all the nine input parameters towards the forecasted result indicates the high contributor parameter.

7. Conclusions and Future Recommendations

This study describes the application of supervised machine learning approaches to predict the compressive strength of concrete containing recycled coarse aggregate (RCA). The gene expression programming (GEP) and artificial neural network (ANN) algorithms were employed for forecasting the compressive strength of concrete. The GEP model was more effective in terms of prediction as compared to the ANN model, which is confirmed from its higher value of linear correlation coefficient (R^2) and lesser values of the errors. The following conclusions can be drawn.

The results of the GEP model indicate the high performance towards the prediction of concrete containing recycled coarse aggregate (RCA) as opposed to the ANN model.

The results from the ANN model are also in the acceptable range and can be used for predicting the outcomes.

The high performance of the GEP model has also been confirmed from statistical checks and the k-fold cross-validation process.

The application of GEP and ANN was proposed in this study to predict the strength property of concrete. The use of ML approaches can predict the strength properties without casting the samples in the laboratory. However, the use of other supervised machine learning algorithms would give a better idea about the accuracy of the employed ML techniques.

The RCA also showed a significant effect (41.1%) towards predicting the concrete's compressive strength compared to other input variables.

It would be easier to understand the effect of the models by making comparisons of more than two algorithms towards the prediction of the outcomes.

It is recommended for future research that datasets should be enhanced from experimental work, field tests, and other numerical analyses using different approaches (e.g., Monte–Carlo simulation).

The input parameters can also be increased by adding the environmental effects (e.g., high temperature and humidity) to provide a better response from the models.

The application of the other ensemble ML algorithms (e.g., Adaboost, bagging, and boosting) can be more effective to predict the compressive strength of concrete.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
165	370	650	850.5	364.5	2.22	20	2400	4.9	50.6
165	370	650	607.5	607.5	2.22	20	2400	4.9	50.8
165	370	650	0	1215	2.22	20	2400	4.9	50.2
165	460	575	850.5	364.5	2.22	20	2400	4.9	60.8
165	460	575	607.5	607.5	2.22	20	2400	4.9	61.2
165	460	575	0	1215	2.22	20	2400	4.9	60.2
165	560	495	850.5	364.5	2.59	20	2400	4.9	70.2
165	560	495	607.5	607.5	2.59	20	2400	4.9	70.8
165	560	495	0	1215	2.59	20	2400	4.9	70
180	500	486.6	0	1135.4	0	16	0	0	44.5
180	500	0	0	1574.3	0	16	0	0	38.7
180	500	486.6	0	1135.4	0	16	0	0	46.1
180	500	0	0	1574.3	0	16	0	0	42.4
180	500	486.6	0	1135.4	0	16	0	0	52.5
180	500	0	0	1574.3	0	16	0	0	50.7
180	500	486.6	0	1135.4	0	16	0	0	45.2
180	500	0	0	1574.3	0	16	0	0	42
180	500	486.6	0	1135.4	0	16	0	0	49.6
180	500	0	0	1574.3	0	16	0	0	45.1
180	500	509.6	0	1135.4	0	16	0	0	54.4
180	500	0	0	1574.3	0	16	0	0	48.2
207.6	400	662	863	153	0	20	2410	5.8	38.1
207.6	400	662	697	298	0	20	2410	5.8	37
207.6	400	662	383	573	0	20	2410	5.8	35.8
207.6	400	662	0	903	0	20	2410	5.8	34.5
217	353	660	861	209	0	20	2330	6.3	44.9
229	353	647	527	513	0	20	2330	6.3	44.7
241	353	625	0	993	0	20	2330	6.3	46.8
230	353	661	853	202	0	20	2330	6.3	43.2
247	353	647	524	496	0	20	2330	6.3	39.7
271	353	625	0	959	0	20	2330	6.3	43.3
206	353	661	864	216	0	20	2330	6.3	43
207	353	649	531	531	0	20	2330	6.3	38.1

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
165	300	765	905	267	4.98	25	2430	4.4	42
165	318	739	608	537	6.042	25	2430	4.4	41
162	325	683	0	1123	6.175	25	2430	4.4	40
160.6	380	598	1182	52	4.9	20	2165	6.8	62.2
165.4	380	529	1175	103	4.9	20	2165	6.8	58.4
170.2	380	460	1168	154	4.9	20	2165	6.8	61.3
175.6	380	327	1162	254	4.9	20	2165	6.8	60.8
180.9	380	0	1162	509	4.9	20	2165	6.8	61
225	410	642	840	204	0	20	2570	3.5	45.3
225	410	642	524	506	0	20	2570	3.5	42.5
225	410	642	210	814	0	20	2570	3.5	39.2
225	410	642	0	1017	0	20	2570	3.5	37.1
180	400	708	886	215	0	20	2570	3.5	62.4
180	400	708	554	538	0	20	2570	3.5	55.8
180	400	708	0	1075	0	20	2570	3.5	42
225	410	642	840	204	0	20	2570	3.5	45.3
225	410	642	524	506	0	20	2570	3.5	42.5
225	410	642	0	1017	0	20	2570	3.5	38.1
234	360	705	0	1100	0	19	2390	4.4	22.1
190	380	705	0	1100	0	19	2390	4.4	25.1
192	400	705	0	1100	0	19	2390	4.4	27.2
181	420	705	0	1100	0	19	2390	4.4	28.7
184	460	705	0	1100	0	19	2390	4.4	29.5
178	264	835	0	1030	0	30	2520	3.8	18
174	262	830	0	1020	0	30	2510	3.9	15.4
148	427	760	0	1000	4.2	30	2520	3.8	36.4
153	423	755	0	990	4.1	30	2510	3.9	35.7
152	443	855	0	885	3.9	30	2520	3.8	44.4
225	410	642	840	204	0	20	2580	3.5	45.3
225	410	642	524	506	0	20	2580	3.5	42.5
225	410	642	0	1017	0	20	2580	3.5	38.1
205	410	662	865	210	0	20	2580	3.5	51.7
205	410	662	541	525	0	20	2580	3.5	47.1
205	410	662	0	1049	0	20	2580	3.5	43.4
180	400	708	886	215	5.6	20	2580	3.5	62.4
180	400	708	554	538	5.6	20	2580	3.5	56.8
180	400	708	0	1075	5.6	20	2580	3.5	52.1
160	400	729	912	221	7.8	20	2580	3.5	69.6
160	400	729	570	554	7.8	20	2580	3.5	65.3
160	400	729	0	1107	7.8	20	2580	3.5	58.5
175	350	730	711	297	1.68	25	2530	1.9	36.7
175	350	730	508	494	1.68	25	2530	1.9	38
175	350	730	0	989	1.68	25	2530	1.9	36
175	350	730	711	282	1.68	25	0	0	32.6
175	350	730	508	469	1.68	25	2400	6.2	30.4
175	350	730	0	938	1.68	25	2400	6.2	29.5
190	380	744.45	756.97	189.24	2.66	20	2338	5.2	47.4
190	380	709.54	471.13	471.12	2.66	20	2338	5.2	47.3
190	380	714.56	0	874.04	5.32	20	2338	5.2	54.8
140	350	732	519	556	4.2	12	2420	6.8	43.3
153	340	723	512	549	3.4	12	2400	6.8	39.6
165	330	715	507	543	2.64	12	2400	6.8	38.1
176	320	708	502	537	1.92	12	2400	6.8	34.5
186	310	702	497	533	1.24	12	2400	6.8	31.6
140	350	732	553	523	4.2	22	2420	8.8	46.1

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
153	340	723	547	517	3.4	22	2420	8.8	45.8
165	330	715	541	511	2.64	22	2420	8.8	39.9
176	320	708	535	506	1.92	22	2420	8.8	36.3
186	310	702	531	501	1.24	22	2420	8.8	34.7
186	372	617.65	1030.22	257.56	0	20	2400	0	27.2
186	372	617.65	772.67	515.55	0	20	2400	0	26.5
186	372	617.65	515.11	772.67	0	20	2400	0	25.4
186	372	617.65	257.56	1030.22	0	20	2400	0	25.1
186	372	494.12	128.78	123.53	0	20	2630	0	26.4
186	372	370.59	128.78	247.06	0	20	2630	0	25.9
186	372	247.06	128.78	370.59	0	20	2630	0	23.5
186	372	123.53	128.78	494.12	0	20	2630	0	15.4
200	270	750	675	200	1.08	19	2440	5.8	18.5
210	270	750	450	400	1.35	19	2440	5.8	18
220	270	750	225	600	1.62	19	2440	5.8	16.5
165	370	865	760	230	1.48	19	2440	5.8	33
165	370	865	505	455	1.85	19	2440	5.8	34.5
165	370	865	250	680	2.59	19	2440	5.8	34
178.5	275	938.05	723.07	180.77	1.925	16	2400	5	31.7
178.5	275	962.73	423.77	423.77	1.925	16	2400	5	32.4
178.5	275	1005.18	0	756.46	1.925	16	2400	5	30.1
190	380	794.31	750.04	187.57	2.66	16	2400	5	43.7
190	380	811.37	443.71	443.71	2.66	16	2400	5	37.5
190	380	838.29	0	807.97	2.66	16	2400	5	40.5
151	335	630	414	720	1.266	19	2420	5.4	41.4
156	349	888	0	792	1.67616	19	2420	5.4	43.9
161	358	645	281	813	1.3584	19	2500	3.3	44.8
156	349	857	0	867	1.2564	19	2500	3.3	45.9
172.43	401	574	911	303	0.2005	20	2661	1.9	47
172.43	401	574	585	585	0.70175	20	2602	2.6	46
172.43	401	574	0	1119	0.90225	20	2510	3.9	42.5
190.8	424	770	0	980	0	19	2490	4.8	41
192.5	350	800	0	1015	0	19	2490	4.8	33.3
191.75	295	814	0	1039	0	19	2490	4.8	24.8
150	250	762	858	286	4.375	19	0	0	26.7
150	250	753	564	564	4.375	19	0	0	21.5
150	250	743	279	836	4.375	19	0	0	21.4
150	250	734	0	1100	4.375	19	0	0	20
180	400	685	770	257	3	19	0	0	38.3
180	400	676	507	507	3	19	0	0	37
180	400	667	250	751	3	19	0	0	35
180	400	659	0	988	3	19	0	0	33.3
175	325	0	0	1762	3.45	32	2263	6	33.2
222	350	0	0	1778	4.5	32	2283	4.2	35.6
221	350	0	0	1771	4.5	32	2292	4.3	34.6
195	325	0	0	1710	3.25	32	2301	5	37.3
123	300	0	192	1728	3	32	2609	1.5	45.4
144	325	0	768	1152	3.25	32	2518	2.7	54.3
123	325	0	754.4	1131.6	3.25	32	2584	1.6	54.4
132	300	0	1448.25	482.75	3	32	2594	1.6	53.4
180	275	625	882	378	0	20	2340	5.3	20
180	295	595	635	635	0	20	2340	5.3	19
180	310	610	0	1240	0	20	2340	5.3	18
180	330	585	872	373	0	20	2340	5.3	23
180	355	560	623	623	0	20	2340	5.3	24
180	372	536	0	1252	0	20	2340	5.3	21

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
180	355	560	872	373	0	20	2340	5.3	25
180	385	550	613	613	0	20	2340	5.3	29
180	409	525	0	1226	0	20	2340	5.3	30
180	375	544	869	372	0	20	2340	5.3	39
180	405	508	624	624	0	20	2340	5.3	31
180	426	494	0	1241	0	20	2340	5.3	34
193	350	661	1061	57	0	12	2010	10.9	40
194	350	515	1061	170	0	12	2010	10.9	38.6
196	350	368	1061	283	0	12	2010	10.9	37.6
199	158	0	1061	566	0	12	2010	10.9	38.6
158	350	693	1111	59	3.5	12	2010	10.9	53.7
163	350	536	1105	177	3.5	12	2010	10.9	51
168	350	381	1100	294	3.5	12	2010	10.9	47.8
178	350	0	1089	582	3.5	12	2010	10.9	45.1
137	350	713	1143	61	3.5	12	2010	10.9	64.6
139	350	555	1143	183	3.5	12	2010	10.9	65.4
143	350	395	1138	304	3.5	12	2010	10.9	63.2
150	350	0	1132	605	3.5	12	2010	10.9	63
180	281	802	0	970	0	10	2360	4.7	38.6
170	293	648	0	919	0	10	2280	6.2	38.1
165	337	841	0	879	0	10	2220	7.8	39.3
190	463	621	0	970	0	10	2360	4.7	60.1
190	500	621	0	919	3.24	10	2280	6.2	60.2
180	600	567	0	879	5.04	10	2220	7.8	62.8
220	537	693	782	138	0	20	2330	4.4	50.8
220	537	693	644	276	0	20	2330	4.4	44.9
220	537	693	506	414	0	20	2330	4.4	44.6
220	537	693	368	552	0	20	2330	4.4	42.4
220	537	693	782	138	0	20	2370	4	54
220	537	693	644	276	0	20	2370	4	56
220	537	693	506	414	0	20	2370	4	54.4
220	537	693	368	552	0	20	2370	4	40.6
220	537	693	782	138	0	20	2390	3.6	55.2
220	537	693	644	276	0	20	2390	3.6	53.5
220	537	693	506	414	0	20	2390	3.6	56.9
220	537	693	368	552	0	20	2390	3.6	54.7
220	537	693	782	138	0	20	2320	4.6	50.5
220	537	693	644	276	0	20	2320	4.6	48.9
220	537	693	506	414	0	20	2320	4.6	45.8
220	537	693	368	552	0	20	2320	4.6	40
220	537	693	782	138	0	20	2390	3.7	54.4
220	537	693	644	276	0	20	2390	3.7	50.2
220	537	693	506	414	0	20	2390	3.7	49.5
220	537	693	368	552	0	20	2390	3.7	40.4
220	537	693	782	138	0	20	2390	3.5	45
220	537	693	644	276	0	20	2390	3.5	46.9
220	537	693	506	414	0	20	2390	3.5	51.4
220	537	693	368	552	0	20	2390	3.5	53.2
220	537	693	782	138	0	20	2380	3.8	55.3
220	537	693	644	276	0	20	2380	3.8	55.9
220	537	693	506	414	0	20	2380	3.8	52.6
220	537	693	368	552	0	20	2380	3.8	48
220	537	693	782	138	0	20	2380	3.8	49.1
220	537	693	644	276	0	20	2380	3.8	49.9
220	537	693	506	414	0	20	2380	3.8	50.3

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
220	537	693	368	552	0	20	2380	3.8	47.5
220	537	693	782	138	0	20	2400	3.5	43.2
220	537	693	644	276	0	20	2400	3.5	53.7
220	537	693	506	414	0	20	2400	3.5	50
220	537	693	368	552	0	20	2400	3.5	43.3
220	537	693	782	138	0	20	2370	4	52.9
220	537	693	644	276	0	20	2370	4	49.9
220	537	693	506	414	0	20	2370	4	53.7
220	537	693	368	552	0	20	2370	4	46
206	413	606	0	987	0	25	2452	4.1	51
206	413	606	0	987	0	25	2452	4.1	49
206	413	606	0	987	0	25	2452	4.1	48
206	413	606	537	494	0	25	2452	4.1	51
206	413	606	537	494	0	25	2452	4.1	51
206	413	606	537	494	0	25	2452	4.1	51
206	413	606	805	245	0	25	2452	4.1	52
206	413	606	805	245	0	25	2452	4.1	50
206	413	606	805	245	0	25	2452	4.1	49
145.6	520	577.2	0	1040	0	25	2260	7.5	38.3
145.6	520	577.2	0	1040	0	25	2260	7.5	32.9
119.6	520	577.2	0	1040	0	25	2260	7.5	33.2
146.2	430	653.6	0	1032	0	25	2260	7.5	31.3
146.2	430	653.6	0	1032	0	25	2260	7.5	28.4
120.4	430	653.6	0	1032	0	25	2260	7.5	28
145.77	339	728.85	0	1050.9	0	25	2260	7.5	26.5
145.77	339	728.85	0	1050.9	0	25	2260	7.5	23.3
118.65	339	728.85	0	1050.9	0	25	2260	7.5	21.6
144.06	294	767.34	0	1029	0	25	2260	7.5	21.6
144.06	294	767.34	0	1029	0	25	2260	7.5	18
117.6	294	767.34	0	1029	0	25	2260	7.5	18.8
146.91	249	804.27	0	1045.8	0	25	2260	7.5	16.1
146.91	249	804.27	0	1045.8	0	25	2260	7.5	13.4
119.52	249	804.27	0	1045.8	0	25	2260	7.5	13.9
179	275	878	735	184	0	20	2320	5.3	41
179	275	849	455	455	0	20	2320	5.3	44
179	275	868	0	830	0	20	2320	5.3	45
190	380	744	757	189	0	20	2320	5.3	50.5
190	380	710	471	471	0	20	2320	5.3	45
190	380	715	0	874	0	20	2320	5.3	56
179	275	961	740	185	0	20	2320	5.3	33.5
179	275	978	408	408	0	20	2320	5.3	32
179	275	1010	0	640	0	20	2320	5.3	32
190	380	813	767	192	0	20	2320	5.3	44
190	380	822	426	427	0	20	2320	5.3	41
190	380	836	0	683	0	20	2320	5.3	41.5
179	325	799	839	210	0	20	2320	5.3	44
179	325	831	490	490	0	20	2320	5.3	41
179	325	825	0	923	0	20	2320	5.3	33.5
173	385	698	892	223	0	20	2320	5.3	53.5
173	385	742	515	515	0	20	2320	5.3	54
173	385	746	0	963	0	20	2320	5.3	40
159.6	380	862.4	489.3	489.3	5.7	20	2330	6.1	41.6
193.8	380	934.1	0	867.7	6.46	20	2330	6.1	31.4
197.6	380	862.4	489.3	489.3	5.7	20	2330	6.1	35.5
231.8	380	934.1	0	867.7	6.46	20	2330	6.1	26
167.2	380	862.4	489.3	489.3	5.7	20	2320	5.8	44.6

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
193.8	380	934.1	0	867.7	6.46	20	2320	5.8	36.7
235.6	380	934.1	0	867.7	6.46	20	2320	5.8	29.5
155.8	380	818.5	840.9	210.2	4.56	20	2360	3.9	46.1
159.6	380	862.4	489.3	489.3	5.7	20	2360	3.9	45.1
171	380	934.1	0	867.7	6.46	20	2360	3.9	42.9
190	380	818.5	840.9	210.2	4.56	20	2360	3.9	39.3
197.6	380	862.4	489.3	489.3	5.7	20	2360	3.9	39.5
205.2	380	934.1	0	867.7	6.46	20	2360	3.9	37.7
159.6	380	818.5	840.9	210.2	4.56	20	2350	4.5	48.1
163.4	380	862.4	489.3	489.3	5.7	20	2350	4.5	41
152	380	934.1	0	867.7	6.46	20	2350	4.5	38.7
193.8	380	818.5	840.9	210.2	4.56	20	2350	4.5	42.7
197.6	380	862.4	489.3	489.3	5.7	20	2350	4.5	35.4
190	380	934.1	0	867.7	6.46	20	2350	4.5	31.4
159.6	380	818.5	840.9	210.2	4.56	20	2350	4.7	48.5
159.6	380	862.4	489.3	489.3	5.7	20	2350	4.7	45.4
163.4	380	934.1	0	867.7	6.46	20	2350	4.7	37
197.6	380	818.5	840.9	210.2	4.56	20	2350	4.7	41.3
197.6	380	862.4	489.3	489.3	5.7	20	2350	4.7	36.8
212.8	380	934.1	0	867.7	6.46	20	2350	4.7	31.2
159.8	340	556	1020	238	0	20	2336	3.6	50
159.8	340	556	638	596	0	20	2315	3.6	45.3
159.8	340	556	319	894	0	20	2295	3.6	44
137.1	380	927	869.2	202	0	10	2470	3.7	108
146.5	380	927	543.2	505.1	0	10	2470	3.7	104.8
162.3	380	927	0	1010.2	0	10	2470	3.7	108.5
138.2	380	927	869.2	195	0	10	2390	4.9	102.5
149.8	380	927	543.2	487.5	0	10	2390	4.9	103.1
170.4	380	927	0	975.1	0	10	2390	4.9	100.8
139.7	380	927	869.2	187.8	0	10	2300	5.9	104.3
153.1	380	927	543.4	469.4	0	10	2300	5.9	96.8
175	380	927	0	938.8	0	10	2300	5.9	91.2
185.4	309	864	848	211	1.0197	16	2380	6.9	42.9
191.7	320	817.5	538	538	1.056	16	2380	6.9	42.5
201.6	336	785	0	1060	1.1088	16	2380	6.9	40.9
192.5	386	829	808	202	2.0458	16	2380	6.9	51.6
200	399	795	504	504	2.1147	16	2380	6.9	51.6
210	420	738	0	1014	2.226	16	2380	6.9	50.3
205	300	697	0	1075	0	20	2450	3.1	35
205	300	697	0	1027	0	20	2370	7.1	29.2
205	300	697	0	1027	0	20	2360	7.8	27.7
180	350	706	0	1089	0	20	2450	3.1	47.6
180	350	706	0	1041	0	20	2370	7.1	42
180	350	706	0	1041	0	20	2360	7.8	42.9
185	425	696	0	1028	0	20	2450	3.1	60
185	425	696	0	982	0	20	2370	7.1	53.7
185	425	696	0	982	0	20	2360	7.8	53.2
165	485	685	0	1039	0	20	2450	3.1	78.2
165	485	685	0	979	0	20	2370	7.1	71.2
165	485	685	0	982	0	20	2360	7.8	65.4
178.3	358	730.4	783.6	299.3	0.3	19	2570	2.7	33.6
178.3	358	730.4	458.3	598.4	0.3	19	2570	2.7	30.4
178.3	358	730.4	0	1020	0.3	19	2570	2.7	29.1
195	300	787.1	756.4	189.1	0	20	2300	5.2	39.5
195	300	737.4	485.5	485.5	0	20	2300	5.2	40.8
195	300	712.6	0	951.4	0	20	2300	5.2	43.7

Water (kg/m^3)	Cement (kg/m^3)	FA (kg/m^3)	NCA (kg/m^3)	RCA (kg/m^3)	SP (kg/m^3)	SRCA (mm)	DRCA (kg/m^3)	WRCA (%)	Strength (MPa)
195	300	814.4	733	183.2	0	20	2300	5.5	41
195	300	804.2	450.7	450.7	0	20	2300	5.5	38.8
195	300	807.9	0	855.2	0	20	2300	5.5	39.9
214.2	210	929	0	966	0	22	2451	7.8	19.7
196	280	866	0	940	0	22	2387	6.9	35.7
161	350	858	0	974	3.5	22	2362	4.2	66.8
212.1	210	932	0	970	0	22	2456	7.5	21.8
193.2	280	870	0	970	0	22	2455	6.4	36.1
157.5	350	858	0	1029	3.5	22	2496	4.2	68.5
207.9	210	938	0	953	0	22	2401	7.6	21
187.6	280	877	0	988	0	22	2484	5.4	41.1
150.5	350	868	0	982	3.5	22	2363	3.6	70.2
205.8	210	943	0	977	0	22	2447	6.9	23.6
190.4	280	873	0	962	0	22	2458	5.8	39.7
157.5	350	858	0	1016	3.5	22	2464	3.9	66.5
179	275	878	735	184	0	19	2320	5.3	49.3
179	275	849	455	455	0	19	2320	5.3	47.5
179	275	868	0	830	0	19	2320	5.3	53.7
190	380	714	757	189	0	19	2320	5.3	64.8
190	380	710	471	471	0	19	2320	5.3	63.5
190	380	715	0	874	0	19	2320	5.3	65.1
179	275	961	740	185	0	19	2320	5.3	64.8
179	275	978	408	408	0	19	2320	5.3	63.5
179	275	1010	0	640	0	19	2320	5.3	65.1
190	380	813	767	192	0	19	2320	5.3	54.9
190	380	822	426	427	0	19	2320	5.3	51.5
190	380	836	0	683	0	19	2320	5.3	50.3
179	325	799	839	210	0	19	2320	5.3	56.5
179	325	831	490	490	0	19	2320	5.3	48.9
179	325	825	0	923	0	19	2320	5.3	43.1
173	385	698	892	233	0	19	2320	5.3	67.4
173	385	742	515	515	0	19	2320	5.3	61.2
173	385	746	0	963	0	19	2320	5.3	53.7

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