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Estimation of compressive strength of high-strength concrete by random forest and M5P model tree approaches

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ABSTRACT

High strength concrete (HSC) define as the concrete that meets a unique mixture of performance uniformity requirements that cannot be reached routinely using conventional constituents and regular mixing, placing, and curing events. The modeling of such type of concrete is very difficult. In this investigation, the performance of the random forest regression and M5P model tree were compared to estimate the 28th day compressive strength of the HSC. Total data set consists of 83 data out of which 70 % of the total dataset used to train the model and residual 30 % used to test the models. The accuracy of the models was depending upon the three performance evaluation parameters which are correlation coefficient (R), root mean square error (RMSE) and maximum absolute error (MAE). The results recommend that random forest regression is more accurate to predict the compressive strength as compare to M5P model tree. Sensitivity analysis indicates that water (W) and Silica fumes (SF) are the most valuable constituents of the HSC and compressive strength mainly depends on these constituents.

1 Introduction

High strength concretes (HSCs) are a special type of concrete and used widely in construction industries [1] [2]. It is special combination of materials which meets specific requirements of a construction projects [3]. It is also more durable than normal strength concrete (NSC). The behavior of HSC is more complex due to the using of different types of admixtures and chemicals for achieving the higher strength of the concrete [4]. Generally, the compressive strength of concrete is taken on 7th and 28th days from the date of placing the concrete. The testing of the concrete for compressive strength at 28th days

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as standard. The average compressive strength of the HSC on 28th day is more than 60 MPa. These benefits decrease the cost of many large-scale construction projects [5]. The recent scenario suggests the focus on nature of concrete and concrete mixture optimization instead of the concrete compositions versus strength relationship. Various researchers considered the characteristic parameters which affect the compressive strength of HSC. These parameters may be aggregates quality, cement strength, water–cement ratio and water content. Now a days, researchers gave the main focus on utilized the industrial waste i.e. silica fume (SF), Fly ash (FA), Fibers (F) etc. [5]. To calculate the compressive strength (CS), the tests of concrete perform without supplementary cementitious materials such as SF, FA, F, SP (super plasticizers) according to the codes and standards in which the traditional approaches depends. These traditional approaches used for modelling the effect of compressive strength of high strength concrete with assumed analytical equations and it's followed regression analysis by experimental data set [7]. However, these approaches are not easy to use and there are no accurate predictions available in the codes regarding the compressive strength of HSCs.

In recent years, different artificial intelligence techniques such as genetics programming, M5P model tree, SVM, ANN, random forest and ANFIS have become very popular and have been used widely by the various researchers [8-11]. Most of these studies recommend that the accuracy of these artificial intelligence techniques is very high. Several researchers used the M5P model tree [12-15] and random forest [16-19], where, they found that these models gave the best fit results. The focus of this research is on the prediction if the 28th days compressive strength of the high strength concrete with two methods; M5P model tree and random forest regression. Furthermore, sensitivity analysis was done by removing one parameter on each case to find out the impact of that parameter on output. The overview of this investigation is shown in Fig. 1.

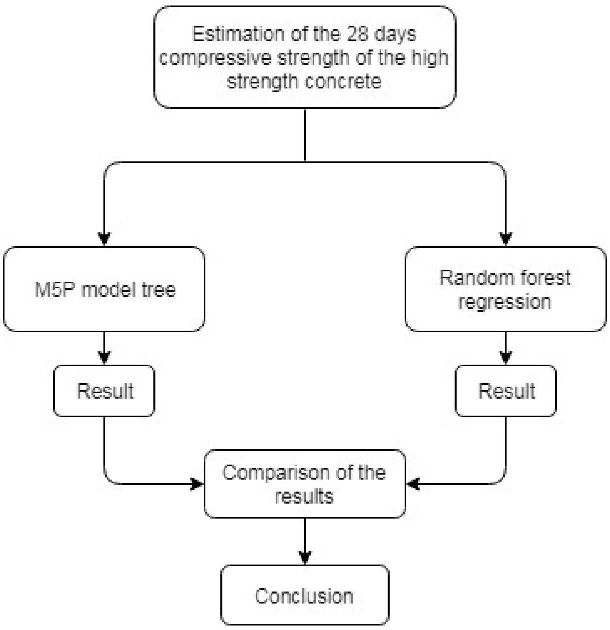


Fig. 1 Overview of this investigation

2 Soft Computing Techniques

2.1 M5P model tree

M5P model Tree is a binary decision tree that uses linear regression function at the leaf (terminal node) which helps in predicting continuous numerical attributes. This method involves two stages for generation of model tree. First stage consists of splitting criteria to generate a decision tree. Splitting criteria for this method is based on treating the standard deviation of class value. Splitting process cause less standard deviation in child node as compared to parent node and thus more pure [20]. Out of all possible splits, M5P model tree opt the one that maximize the error reductions. This process of splitting the data may overgrow the tree which may cause over fitting. So, the next stage involves in removing over fitting using pruning method. It prunes back overgrown trees by substituting the sub trees with linear regression function. In this technique of tree generation, parameter space is split into surfaces and building a linear regression model in each of them. M5P model tree algorithm utilizes standard deviation of the class value reaching at terminal node which measures of the error value at that node and evaluates the expected reduction in error. Formula for standard reduction formula is given as [20]:

$$SDR = sd(N) - \sum \frac{|Ni|}{|N|}.sd(Ni) \quad (1)$$

Where N depicts a set of examples that arrive at the node. Ni depicts i^{th} outcome of subset of examples of potential set and sd is standard deviation.

2.2 Random Forest (RF)

Random forest (RF) regression approach consists of a combination of tree predictors, where each tree is generated from the input vector using a random vector sampled independently. Random forest regression consists of combination of variables at each node to grow a tree or using randomly selected input variable as used in present study. To generate a training data set, bagging, which randomly draw I training samples with replacement, where I is the size of the original training set [21], or a randomly selected part of the training set is used for the construction of individual trees for a random feature combination. In case of bagging (bootstrap sample), about one-third of the data are left out from every tree grown thus training set consists of about 67% of original training set whereas the left out data are called out-of-bag (out of the bootstrap sampling). Random forest uses the Gini Index [22] as attribute selection measure which measures the impurity of the variable compared to the output. Two user-defined parameters are required for random forest regression: number of input variables (m) used at each node to generate a tree and the number of trees to be grown (k). At each node, only selected variables are searched through for the best split. Thus, the random forest regression consists of k trees.

3 Data Set

The data set for the M5P model tree and random forest was collected from published creditable journals.

Table 1. Features of the training and testing dataset

Variable	**Units**	**TRAINING DATA SET**				
		Range	**Mean**	**St.**	**Skewness**	**Kurtosis**
C	Kg/m^3	32-4710	500.81	569.17	7.33	55.14
S	Kg/m^3	7.9-891	707.23	143.57	-2.17	8.94
CA	Kg/m^3	793-1203	1024.10	110.45	-0.34	-0.64
SF	Kg/m^3	0-75	19.68	24.42	0.74	-0.93
FA	Kg/m^3	0-194	36.35	60.42	1.36	0.47
F	Kg/m^3	0-80	17.56	30.12	1.31	0.01
SP	Kg/m^3	0-22.5	7.12	5.13	0.54	-0.25
W	Kg/m^3	126-214	163.73	23.32	0.39	-0.30
AR	%	0-80	21.12	33.61	1.02	-0.87
CS	MPA	50.78-	75.28	13.69	0.09	-0.91
		TESTING DATA SET				
C	Kg/m^3	325-540	434.22	62.36	0.02	-1.06
S	Kg/m^3	448-891	731.50	100.73	-0.75	1.02
CA	Kg/m^3	112-1203	995.18	210.07	-3.26	13.53
SF	Kg/m^3	0-60	18.14	22.61	0.67	-1.24
FA	Kg/m^3	0-224	37.76	66.26	1.80	2.53
F	Kg/m^3	0-80	18.32	27.41	1.41	0.92
SP	Kg/m^3	0-18	6.705	4.580	0.76	0.05
W	Kg/m^3	126-214	161.77	20.71	0.52	0.27
AR	%	0-80	28.36	36.03	0.53	-1.74
CS	MPa	51.44-	76.50	15.09	0.04	-0.77

Data were derived from a number of resources [23-40]. Data were assembled for the high strength concrete containing cement (C), sand (S), course aggregate (CA), Silica fume (SF), Fly ash (FA), Fiber (F), superplasticizers (SP), water (W), aspect ratio (AR) and 28th days compressive strength (CR). The range of the CS was from 50.78 to 105.7 MPa. The total dataset consists of 83 data in which 70% used for the training the dataset and 30% used for the testing. Table 1 furnished the features of the training and testing dataset in which C, S, CA, SF, FA, F, SP, W, and AR were the input parameters and CS was the output parameter.

3.1 Performance evaluation criteria

The preciseness of the estimated values by the both models was quantified by the correlation coefficient (R), root mean square error (RMSE) and maximum absolute error (MAE). The value of correlation coefficient varies from -1 to 1, whereas the values of root means square error and maximum absolute error vary from 0 to infinity. If the value of correlation coefficient is approaching to 1 and the values of root mean square error and maximum absolute error are approaching to 0 the model is most accurate. The formula for determining the correlation coefficient, root means square error and maximum absolute error is as follow:

$$R = \frac{n\sum_{i=1}^{n} x_i . y_i - \left(\sum_{i=1}^{n} x_i\right).\left(\sum_{i=1}^{n} y_i\right)}{\sqrt{n\left(\sum_{i=1}^{n} x_i^2\right) - \left(\sum_{i=1}^{n} x_i\right)^2} . \sqrt{n\left(\sum_{i=1}^{n} y_i^2\right) - \left(\sum_{i=1}^{n} y_i\right)^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} . \sum_{i=1}^{n} \left(x_i - y_i\right)^2} \tag{3}$$

$$MAE = \sqrt{\frac{1}{n} . \sum_{i=1}^{n} \left|x_i - y_i\right|} \tag{4}$$

where x_i is the actual value, y_i is the predicted value and n is the number of observations. The collective used of R, RMSE and MAE provides a satisfactory assessment of every model's performance and allows a comparison of the precision of the two modelling approaches used in the investigation.

4 Result and Discussion

4.1 Input selection

The models listed in Table 2 were created by utilization various combination of inputs.

Table 2. Details of model input and model output with the model number

Model no.	Model input	Model
1	C, S, CA, W	CS
2	SF, FA, F, SP, AR	CS
3	C, SF, F, SP, AR, FA	CS
4	S, SF, FA, SP, AR, F	CS
5	CA, SF, FA, F, AR, SP	CS
6	SF, FA, F, SP, AR, W	CS
7	C, S, CA, W, SF	CS
8	FA, C, S, CA, W	CS
9	C, F, S, W, CA	CS
10	F, C, S, CA, W	CS
11	AR, C, CA, W, S	CS
12	C, S, CA, SF, FA, F, SP, AR, W	CS

Model no. 1 only contained the cement, sand, course aggregates and water which were major constituents of the high strength concrete and model no. 2 contained the silica fume, fly ash, fiber, superplasticizers, and aspects ratio which all were the admixture. In model no. 3 – 6, all model contained above-mentioned admixture and major constituents like cement, sand, course aggregates and water were changed one by one respectively. Similarly, in model no. 7 – 11, all model contained major constituents remain same and admixture changed one by one respectively. Model no. 12 contained the all constituents of the concrete shown in this study. These 12 models have been used to predict the 28th day compressive strength of high strength concrete by M5P model tree and random forest regression techniques.

4.2 M5P Model Tree

The M5P model tree (with parameter 'm') was implemented using WEKA software. The value of 'm' was finding out by error and trial method which suggests that '4' was the optimum value for 'm'. Table 4 suggests the values of the performance evaluation criteria (R, RMSE, and MAE). These values suggest that model no. 8 (dependent variables FA, C, S, CA, W, see Table 2) gave the best prediction with highest value of R (0.807) and lowest values of RMSE and MAE (8.836 and 0.286) with the testing dataset. Figure 2 illustrates that the tree model generated the best scenario (model no. 8). The main advantage of the M5P model tree in prediction of the 28th day compressive strength is that it gives the simple linear equation to predict the compressive strength. Figure 2 explained the applicability of linear model in any kind of compressive strength estimation. For example: if S is greater than 821.5 Kg/m3, CS values must be taken from LM num 2 otherwise from LM num: 1. The details of the LM num: 1 and LM num: 2 are given in Table 3.

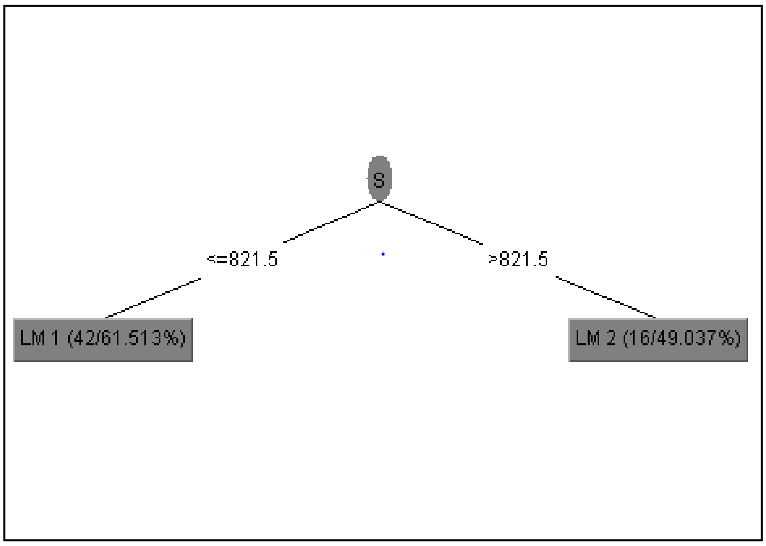


Fig. 2. Tree visualizations for the best model (model no. 8)

Table 3. Linear model provided by M5P tree model

LM num: 1
CS = 0.0775*C -0.0143*S -0.0377*CA +0.0281*FA -0.4658*W +167.1581
LM num: 2
CS = -0.0263*S -0.0288*CA -0.332*W +171.6785

Figure 3 (a) gives the scatters details of the experimentally estimated and predicted values of the 28th day compressive strength of high strength concrete using the M5P model tree with the testing dataset. It is clear from the Figure 3 (a) that all the scatters show the best agreement with the line of the agreement. Similarly, Figure 3 (b) shows the variation of the experimentally estimated and predicted values of 28th day compressive strength, it suggests that the predicted values column have almost the same height with experimentally estimated values column.

Table 4. Results of the different input combination using M5P model tree using training and testing dataset

Model No.	*Training dataset*			*Testing dataset*		
	R	***RMSE***	***MAE***	***R***	***RMSE***	***MAE***
1	*0.812*	*8.156*	*0.131*	*0.783*	*9.890*	*0.389*
2	*0.450*	*12.894*	*0.191*	*0.486*	*13.237*	*0.459*
3	*0.649*	*10.759*	*0.159*	*0.379*	*13.517*	*0.447*
4	*0.649*	*10.254*	*0.154*	*0.507*	*12.682*	*0.419*
5	*0.396*	*12.849*	*0.189*	*0.414*	*13.758*	*0.459*
6	*0.588*	*11.540*	*0.152*	*0.768*	*11.836*	*0.490*
7	*0.827*	*7.822*	*0.108*	*0.792*	*9.253*	*0.290*
8	*0.852*	*7.959*	*0.107*	***0.814***	***8.806***	***0.275***
9	*0.841*	*7.989*	*0.116*	*0.750*	*10.256*	*0.333*
10	*0.832*	*7.957*	*0.121*	*0.771*	*10.007*	*0.351*
11	*0.821*	*7.939*	*0.131*	*0.770*	*10.287*	*0.353*
12	*0.839*	*6.987*	*0.101*	*0.767*	*10.083*	*0.299*

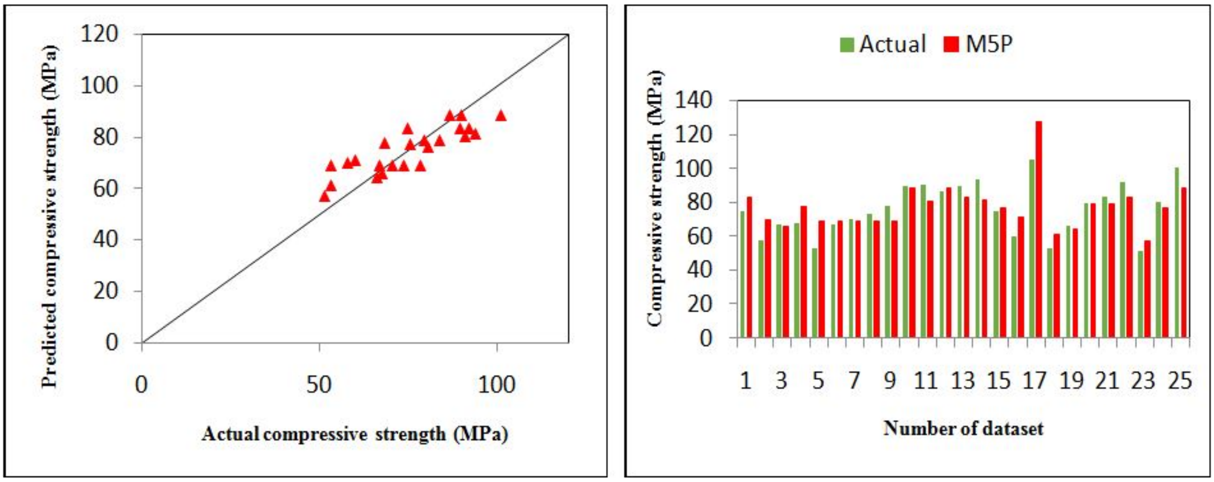


Fig. 3. (a) and (b) Scattered diagram and comparison of actual and predicted values of compressive strength by using M5P model tree in testing dataset

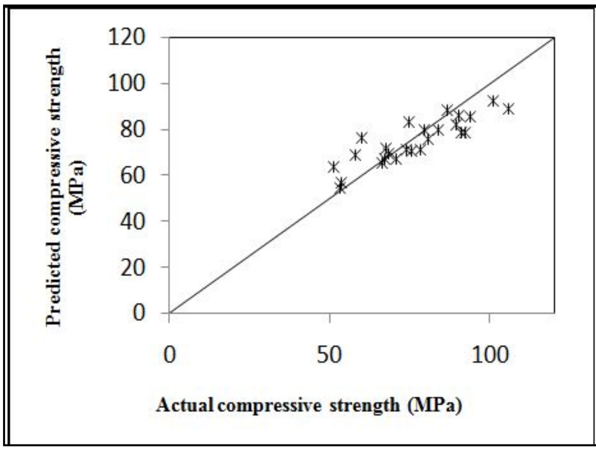
4.3 Random Forest

The random forest regression (with parameter k, m and I) was also implemented using WEKA software. The values of k, m and I also found out by error and trial method which suggests that optimum values of k, m and I were 0, 1 and 500 respectively. Similarly, M5P model tree, the values of the performance evaluation parameters (R, RMSE, and MAE) were listed in Table 5. These values suggest that model no. 7 (dependent variables C, S, CA, W, SF, see Table 2) gave the best prediction with highest value of R (0.876) and lowest values of RMSE and MAE (8.014MPa and 0.255MPa) with the testing dataset.

The scatters detail of the experimentally estimated and predicted values of the 28th day compressive strength of high strength concrete using random forest with testing dataset are shown in Figure 4 (a). Hence, Figure 4(a) clearly shows that all scatters give a best agreement with the line of the agreement. Also, Figure 4 (b) shows the variation of the experimentally estimated and predicted values of 28th day compressive strength, it suggests that predicted values column have almost the same height with experimentally estimated values column.

Table 5. Results of the different input combination using random forest model tree using training and testing dataset

Model No.	*Training dataset*			*Testing dataset*		
	R	***RMSE***	***MAE***	***R***	***RMSE***	***MAE***
1	*0.949*	*4.624*	*0.057*	*0.838*	*8.606*	*0.276*
2	*0.945*	*5.134*	*0.067*	*0.360*	*14.515*	*0.448*
3	*0.967*	*4.557*	*0.063*	*0.608*	*11.997*	*0.390*
4	*0.964*	*4.264*	*0.055*	*0.667*	*11.215*	*0.347*
5	*0.966*	*4.544*	*0.062*	*0.600*	*12.313*	*0.364*
6	*0.960*	*4.560*	*0.061*	*0.773*	*10.481*	*0340*
7	*0.968*	*3.968*	*0.053*	***0.876***	***8.014***	***0.255***
8	*0.949*	*4.674*	*0.058*	*0.825*	*8.893*	*0.287*
9	*0.952*	*4.551*	*0.055*	*0.823*	*8.882*	*0.284*
10	*0.950*	*4.618*	*0.056*	*0.791*	*9.378*	*0.314*
11	*0.963*	*4.163*	*0.052*	*0.760*	*9.811*	*0.314*
12	*0.975*	*3.750*	*0.048*	*0.818*	*9.235*	*0.301*



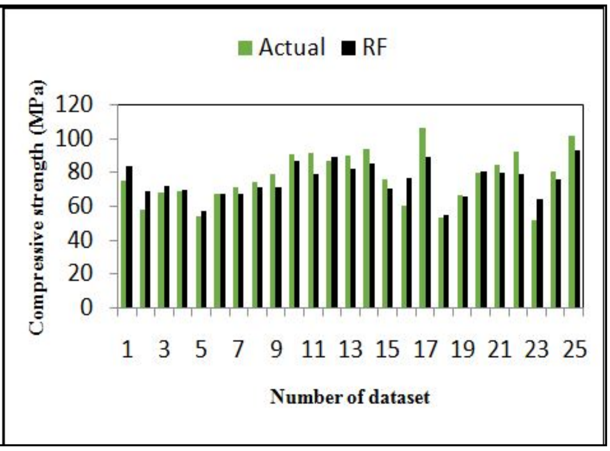


Fig. 4. (a) and (b) Scattered diagram and comparison of actual and predicted values of compressive strength by using random forest regression in testing dataset

4.4 Comparison of Results

All 12 input data model combinations for both modeling approaches are shown in Table 2. The result from both approaches has been concluded in Table 6 which suggests that model no. 8 was the best-fit model to predict the compressive strength accurately in which FA, C, S, CA, W was the main constituents. The overall comparison also suggests that the entire model perform well to predict the compressive strength except for model no. 2 to 5 which gave very low R values and very high RMSE and MAE values.

Based on Table 6, the random forest modeling techniques were highly accurate than M5P model tree which produce higher values of R and lower values of RMSE & MAE in training as well as in testing also. Figures 5 (a) and (b) show the scatters and variation of the predicted values with the actual values of the compressive strength of HSCs. The representation of this figure clearly reflects that random forest regression gave the perfect prediction as compared to the M5P model tree.

Table 6. Performance measured for different modeled compressive strength

Techniques	*Model No.*	*Training*			*Testing*		
		R	***RMSE***	***MAE***	***R***	***RMSE***	***MAE***
M5P model tree	*Model No. 8*	*0.816*	*7.948*	*0.109*	*0.807*	*8.836*	*0.286*
Random forest	*Model no. 7*	*0.968*	*3.968*	*0.053*	*0.876*	*8.014*	*0.255*

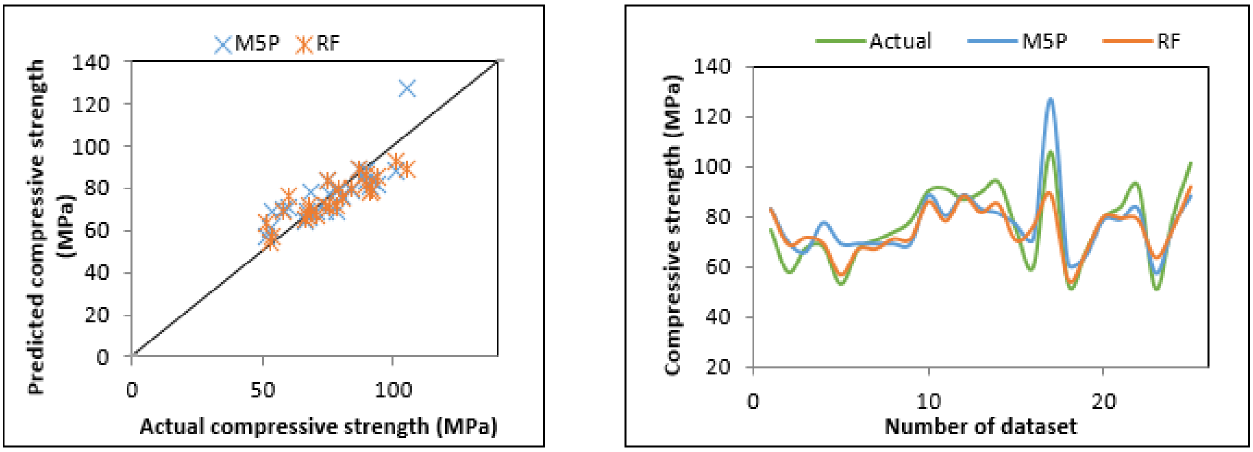


Fig. 5. (a) and (b) Scattered diagram and comparison of actual and predicted values of compressive strength by using M5P model tree and random forest regression in testing dataset

4.5 Sensitivity Investigation

Sensitivity investigation tests were conducted using random forest regression model to decide the relative importance of each of the input parameters on compressive strength of high strength concrete. Water (W) and Silica fume (SF) mainly affect the compressive strength. Various combinations shown in Table 7 were considered by removing one parameter in each case and its influence on the estimation of compressive strength was recorded in terms of the R and RMSE as main performance criteria. Table 5 compares the performance of random forest regression model with different input combinations using same user-defined parameters.

Table 7. Results of sensitivity investigation using random forest regression

Model	*Inputs*	*Remove*	*Output*	*R*	*RMSE*
1	*C, S, CA, SF, FA, F, SP, AR, W*	*-*	*CS*	*0.818*	*9.235*
2	*S, CA, SF, FA, F, SP, AR, W*	*C*	*CS*	*0.801*	*9.497*
3	*C, CA, SF, FA, F, SP, AR, W*	*S*	*CS*	*0.788*	*9.797*
4	*C, S, SF, FA, F, SP, AR, W*	*CA*	*CS*	*0.814*	*9.254*
5	*C, S, CA, FA, F, SP, AR, W*	*SF*	*CS*	*0.704*	*10.681*
6	*C, S, CA, SF, F, SP, AR, W*	*FA*	*CS*	*0.819*	*9.116*
7	*C, S, CA, SF, FA, SP, AR, W*	*F*	*CS*	*0.823*	*9.101*
8	*C, S, CA, SF, FA, F, AR, W*	*SP*	*CS*	*0.846*	*8.792*
9	*C, S, CA, SF, FA, F, SP, W*	*AR*	*CS*	*0.841*	*8.733*
10	*C, S, CA, SF, FA, F, SP, AR,*	*W*	*CS*	*0.705*	*10.866*

5 Conclusion

The performances of two regression-based modelling approaches described by this investigation to deliver evidences for appropriate approaches for predicting the compressive strength of HSC. These approaches were M5P model tree and random forest regression. This investigation used several combination models as an input and compressive strength as output out of which model no. 7 and 8 are highly efficient with random forest regression and M5P model tree respectively.

The investigation shows that random forest regression approach has an edge over M5P model tree in predicting the compressive strength of HSCs. The R values come from the random forest regression approaches (0.876) is much higher than M5P model tree (0.807). Similarly, the values of RMSE and MAE come from the random forest regression (8.014 MPa and 0.255 MPa are much lower than M5P model tree (8.836 MPa and 0.286 MPa)). Hence, random forest regression gave the more accurate prediction to predict the compressive strength as compared to the M5P model tree. Sensitivity investigation suggests that water (W) and Silica fume (SF) are the major influencing parameters in the estimation of 28th day compressive strength of high strength concrete for this data set.

Random forest regression approach is a flexible approach which is the main advantage of this approach. The implementation of random forest is time consumable but it took less time than experimental estimation of the compressive strength of HSCs. Hence, the proposed random forest model decreases design cost, saves time and reduces the waste material.

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