International Journal of Sustainable Built Environment (2014) 3, 187–198

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Gulf Organisation for Research and Development

International Journal of Sustainable Built Environment

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Original Article/Research

Modeling compressive strength of recycled aggregate concrete by Artificial Neural Network, Model Tree and Non-linear Regression

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Received 31 August 2014; accepted 4 December 2014

Abstract

In the recent past Artificial Neural Networks (ANN) have emerged out as a promising technique for predicting compressive strength of concrete. In the present study back propagation was used to predict the 28 day compressive strength of recycled aggregate concrete (RAC) along with two other data driven techniques namely Model Tree (MT) and Non-linear Regression (NLR). Recycled aggregate is the current need of the hour owing to its environmental friendly aspect of re-use of the construction waste. The study observed that, prediction of 28 day compressive strength of RAC was done better by ANN than NLR and MT. The input parameters were cubic meter proportions of Cement, Natural fine aggregate, Natural coarse Aggregates, recycled aggregates, Admixture and Water (also called as raw data). The study also concluded that ANN performs better when non-dimensional parameters like Sand–Aggregate ratio, Water–total materials ratio, Aggregate–Cement ratio, Water–Cement ratio and Replacement ratio of natural aggregates by recycled aggregates, were used as additional input parameters. Study of each network developed using raw data and each non dimensional parameter facilitated in studying the impact of each parameter on the performance of the models developed using ANN, MT and NLR as well as performance of the ANN models developed with limited number of inputs. The results indicate that ANN learn from the examples and grasp the fundamental domain rules governing strength of concrete.

Keywords: Recycled aggregates; Recycled aggregate concrete; Artificial Neural Network; Model Tree; Non-linear Regression

1. Introduction

Scarcity of natural resources is a growing environmental concern and there is a need to reduce the impact of this scarcity and take a step toward conserving the environment. A possible solution to reduce this impact may be the use of C&D (Construction and demolition) waste as replacement to natural resources in concrete mixes. C&D waste, especially the concrete waste can be made to recycled aggregates (RA), which can be used in concrete as aggregates. RA is a material derived from waste concrete which is produced by a two stage crushing of demolished concrete followed by screening and removal of contaminants such as reinforcement, wood, plastics, etc. (Rao et al., 2010). When recycled aggregates are used in a

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Peer review under responsibility of The Gulf Organisation for Research and Development.

http://dx.doi.org/10.1016/j.ijsbe.2014.12.002
2212-6090/

concrete mix the concrete is termed as recycled aggregate concrete (RAC).

Several researches have studied the influence of RA on concrete properties such as compressive strength, tensile strength, etc. (Ajdukiewiez and Kliszczewicz, 2002; Hansen and Narud, 1983; Tsung et al., 2006; Ryu, 2002). RA is heterogeneous in nature as they contain attached mortar to the aggregates. This property of RA limits its use in concrete, as it decreases the compressive strength of RAC. Surrounding mortar on the aggregate tends to increase water absorption and reduce the density of RAC and becomes the governing criteria for the compressive strength of concrete with recycled aggregates (Ajdukiewiez and Kliszczewicz, 2002; Hansen and Narud, 1983; Tsung et al., 2006; Ryu, 2002). It was also observed that the workability of concrete made using RA is less as compared to workability of concrete made using normal aggregates may be due to more water absorption in the former (Yong and Teo, 2009). To add to it RA in concrete as a replacement to natural aggregates tends to reduce the compressive strength of concrete may be due to weaker bond between mortar and RCA. (Akbari et al., 2011). A similar study concluded that using different recycled aggregates RA replacement ratios, W/C ratios and RAs with different strengths and different moisture conditions, the strength of RAC was about 10–25% lower than that of natural aggregate concrete (NAC) and thus 100% replacement of RA tends to lower the strength of concrete (Ajdukiewiez and Kliszczewicz, 2002; Hansen and Narud, 1983; Tsung et al., 2006; Ryu, 2002) and therefore should be avoided. The study also concluded that the compressive or tensile strength loss of RAC prepared with low strength RA was more significant than that of concrete prepared with high strength RA, and the extent of the reduction was related to many parameters, such as the type of concrete used for making the RA (high, medium or low strength), replacement ratios, water–cement ratios and the moisture conditions of the RA (Ajdukiewiez and Kliszczewicz, 2002). Thus the diverse behavior of RA and RAC demands their extensive testing to have more insights into their behavior pattern. However extensive testing demands amounts of materials, time and cost. Thus to improve the studies and to reduce the cost and time required for testing, models based on experimental data predicting the compressive strength of RAC with an acceptable range of error may be encouraged. Many techniques such as Artificial Neural Networks, Regression analysis, etc. were used earlier to predict the compressive strength of RAC. The relationships among demolished concrete characteristics, properties of their RA and strength of their RAC were established using regression analysis (Vivian et al., 2008). ANN models were developed to predict the strength and slump of ready mixed concrete and high strength concrete, in which chemical admixtures and or mineral additives were used (Dias and Pooliyadda, 2001; I-Cheng, 2007). Particularly in the field of RAC, ANN was used to predict strength of recycled aggregate concrete (Adriana et al., 2013). Besides ANN other data driven techniques such as Linear Regression analysis and Model Trees (MT) were used to model compressive strength of concrete (Deepa et al., 2010). The study concluded that ANN facilitates a better correlation among inputs and output. However MT though showed a less correlation has an advantage of providing equations.

In the current study three techniques, Artificial Neural Networks (ANN), Model Tree (MT) and Non-linear Regression (NLR) are used with raw data and non-dimensional parameters as inputs and 28 day compressive strength of concrete as output. The major objective of the study can be stated as:

(i) To explore the possibility of predicting strength of concrete with limited number of inputs, i.e., by using raw data or mandatory parameters, using the techniques of ANN, MT and NLR.
(ii) To develop models for predicting compressive strength of RAC using raw data and non-dimensional parameters as input parameters, using each of the above said techniques and understand the performance and influence of each additional input parameter on output.

Basic concepts of ANN, MT and NLR are discussed in the next section followed by information about data adopted for the current study. The methodology for model development is then presented followed by results and discussion. The conclusions are presented at the end.

2. Modeling techniques

In the current study, prediction of recycled aggregate concrete strength is done using Artificial Neural Networks, Model Tree with M5 algorithm and Non-linear Regression. These approaches are described in brief below.

2.1. Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) is a soft computing technique involving an input layer, one or more hidden layer (s) and an output layer. The hidden layer is connected to the other layers by weights, biases and transfer functions. An error function is determined by the difference between network output and the target. The error is propagated back and the weight and biases are adjusted using some optimization technique which minimizes the error. The entire process called training is repeated for number of epochs till the desired accuracy in output is achieved. Once the network is trained it can be used to validate against unseen data using trained weights and biases (Londhe et al., 2009). Readers are referred to Londhe et al. (2009) for details of ANN.

2.2. Model Tree

MT is a technique which generates an equation at each node. The divide-and-conquer approach partitions the data and provides rules for reaching the models at the leaf nodes. The linear models are then used to quantify the contribution of each attribute to the overall predicted value. M5P is a reconstruction of Quinlan's M5 algorithm for inducing trees of regression models. M5P combines a conventional decision tree with the possibility of linear regression functions at the nodes. First, a decision-tree induction algorithm is used to build a tree, but instead of maximizing the information gained at each inner node, a splitting criterion is used that minimizes the intra-subset variation in the class values down each branch. The splitting procedure in M5 stops if the class values of all instances that reach a node vary very slightly, or only a few instances remain. Second, the tree is pruned back from each leaf. When pruning an inner node is turned into a leaf with a regression plane. Model Trees are a sub-class of regression trees having linear models at the leaf node. In comparison with classical regression trees, Model Trees deliver better compactness and prediction accuracy. These advantages issue from the ability of Model Trees to leverage potential linearity at leaf nodes (Deepa et al., 2010). Readers are referred to Londhe and Charhate (2010) for details.

2.3. Non-linear Regression

Non-linear Regressions determine the relationship between two or more independent variables and a dependent variable by fitting a linear equation to the observed data. Every value of the independent variable is associated with a value of the dependent variable. A general form of multiple linear regressions is given as:

$$\mathrm{Y} = \mathrm{a}_0 + \mathrm{a}_1 * \mathrm{X}_1 + \mathrm{a}_2 * \mathrm{X}_2 \ldots \mathrm{a}_n * \mathrm{X}_n \tag{1}$$

However for situations where multiple dependencies are non-linear, the logarithmic transformation can be applied to this type of regression:

$$\begin{aligned}\mathrm{Log}(\mathrm{Y}) = {} & \mathrm{Log}(\mathrm{a}_0) + \mathrm{a}_1 * \log(\mathrm{X}_1) + \mathrm{a}_2 * \log(\mathrm{X}_2) \\ & + \mathrm{a}_3 * \mathrm{Log}(\mathrm{X}_3) \ldots \mathrm{a}_n * \mathrm{Log}(\mathrm{X}_n)\end{aligned} \tag{2}$$

This equation can be transformed back to a form that predicts the dependent variable Y by taking antilogarithm to yield an equation of type:

$$\mathrm{Y} = \mathrm{a}_0 * \mathrm{X}_1^{\mathrm{a}_1} * \mathrm{X}_2^{\mathrm{a}_2} \ldots \mathrm{X}_n^{\mathrm{a}_n} \tag{3}$$

where a_0, a_1, $a_2 \ldots a_n$ are coefficients and X_1, $X_2 \ldots X_n$ are inputs or independent parameters.

This is called the multivariable power equation and in engineering, variables are often dependent on several independent variables, this functional dependency is best characterized by the equation mentioned earlier, and is said to give results that are more realistic too (Zain and Abd, 2009).

The current work, reports the results of the study conducted on 10 models developed using each of the above mentioned techniques to evaluate the 28 day compressive strength of recycled aggregate concrete. Comparative analysis of the results was also done to identify the better technique for predicting the compressive strength.

3. Data

The data used in the present study was obtained from fresh experiments done by authors and from the published literature (Rao et al., 2010; Ajdukiewiez and Kliszczewicz, 2002; Hansen and Narud, 1983; Tsung et al., 2006; Ryu, 2002; Yong and Teo, 2009; Akbari et al., 2011; Padmini et al., 2003; Amnon, 2003; Sangeeta et al., 2011; Dapena et al., 2011; Valeria, 2010; Fathifazl et al., 2009; Hasbi and et al., 2011; Brett et al., 2011; Evangelista and de Brito, 2010; Claudio and Angel, 2003; Kou, 2006; Poon et al., 2004; Duangthidar et al., 2010; Suraya et al., 2011; Domingo et al., 2009; Pereira et al., 2012; Agarwal et al., 2011; Luís et al., 2004; Arlindo et al., 2004). A total of 257 data sets were available which mainly contained proportions of materials (called as raw data) used for making concrete with conventional materials and concrete with RA. Various parameters used in the study were divided into mandatory parameters and non-dimensional parameters as shown below.

1. *Mandatory input parameters called as raw data:* As per standard mix design procedures followed all over the world, weights per cubic meter are calculated and are treated as raw data (Shetty, 2005; Zongjin, 2011). The parameters were Cement (C), Natural fine aggregate (NFA), Recycled fine aggregate (RFA), Natural coarse Aggregate-20 mm (NC20), Natural coarse Aggregate-10 mm (NC10), Recycled coarse Aggregate 20 mm (RCA20), Recycled coarse Aggregate-10 mm (RCA10), Admixture(A),Water(W) (Shetty, 2005; Zongjin, 2011). These input parameters remained same for all the models.
2. *Non-dimensional input parameters:* Water–Cement ratio (W/C), Sand–Aggregate ratio (S/A), Water to total materials ratio (W/T), Replacement ratio, of recycled aggregate to natural aggregate by volume (RR) and Aggregate to Cement ratio (A/C) derived from the raw data (the non-dimensional parameters) used for ANN and MT and NLR models as input parameters.
3. *Output parameter or dependent variable:* 28 day compressive strength of recycled concrete aggregate was termed as output parameter for ANN and MT and dependent variable for NLR.

The maximum and minimum values of input and output parameters are shown in Table 1.

Table 1
Input and output parameters with their maximum and minimum values.

Sr. No		Range of Values (Min–Max)
Input parameters		
1	Cement Content (C) (kg/m^3)	235–645
2	Natural Fine Aggregate (NFA) (kg/m^3)	0–1050
3	Recycled fine aggregate (RFA) (kg/m^3)	0–1050
4	Natural coarse Aggregates-20 mm (NCA-20) kg/m^3	0–1508.64
5	Natural coarse Aggregates-10 mm (NCA-10) kg/m^3	0–553
6	Recycled coarse Aggregates-20 mm (RCA-20) kg/m^3	0–1508.64
7	Recycled coarse Aggregates-10 mm (RCA-10) kg/m^3	0–840
8	Water content (W) (kg/m^3)	120–358
9	Admixture (A) (kg/m^3)	0–10.4
10	Aggregate to Cement ratio (A/C)	2.279–9.237
11	Water–Cement ratio (W/C)	0.299–1.028
12	Sand–Aggregate ratio (S/A)	0.149–1.566
13	Replacement ratio (RR) (%)	0–100
14	Water to total materials (W/T)	11.287–11.553
Output parameter		
1	28 day compressive strength of concrete (N/mm^2)	10.319–100.5

4. Methodology used for model development

In the current study ten different models were developed using each of the techniques viz. ANN, MT and NLR to predict the 28 day strength of RAC. The first task was to determine the input parameters or independent variables (except mandatory parameters) for each kind of model which was achieved by the correlation analysis between each non-dimensional input parameter or independent variable and the 28 day compressive strength of concrete. The correlation coefficients showing the linear relation between input parameter and output parameter are as shown in Fig. 1.

To facilitate the easy understanding of relationship of each input with the output through ANN, the networks were divided into two sets. In set 1, ANN1, MT1 and NLR1 were the models with respective techniques and raw data as their input parameters. Further in ANN2, MT2 and NLR2 with raw data, S/A was added as additional parameter as it shows the highest correlation with output. This allowed to study the influence of S/A on the performance of network. In a similar way further non-dimensional parameters Water–Cement ratio (W/C), Water to total materials ratio (W/T), Replacement ratio of recycled aggregate to natural aggregate by volume (RR) and Aggregate to Cement ratio (A/C) were added and separate networks were formed for each of them (ANN 1 to ANN 6). The details of set 1 can be seen in Table 2.

In set 2, with ANN1, MT1 and NLR1 as the first models, each non-dimensional parameter or independent variables were added one by one in subsequent models according to the decreasing order of their correlation with 28 day compressive strength of concrete. Thus in set 2 ANN7, MT7 and NLR7 were the first models with having S/A and W/T as the non-dimensional parameters or independent parameters. Subsequently remaining non-dimensional parameters or independent parameters were added, as RR for ANN8, MT8 and NLR8, A/C for ANN9, MT9 and NLR9 and W/C for ANN10, MT10 and NLR10. This allowed us to study the combined effect of each additional parameter on the performance of models. The methodology adopted for each model is shown in Table 3.

For each model in ANN three layered "Feed forward Back propagation" network was developed to predict the 28 day compressive strength of RAC and trained till a very low performance error (mean squared error) was achieved. It should be noted that the optimal number of neurons in hidden layers was determined by the training process. All the networks were trained using Levenberg–Marquardt algorithm with 'log-sigmoid 'transfer functions in between first (input) and second (hidden) layers and 'linear' transfer function between the second and third layers (output). Further the performance of the developed models was assessed by statistical measures like correlation coefficient (r), Normalized root mean squared error (NRMSE), Average absolute error (AARE) and Nash–Sutcliffe Efficiency (E), details of which are given in (Shetty, 2005; Zongjin, 2011; Hong and Ji-Zong, 2000; David and Gregory, 1999; Jain et al., 2008). From the available data 70% of data were used for training, 15% for validation and 15% for testing. The data division remains same for MT and NLR models too.

For Model Tree as a technique, M5 algorithm was used for calibrating the model. Readers are referred to (Quinlan

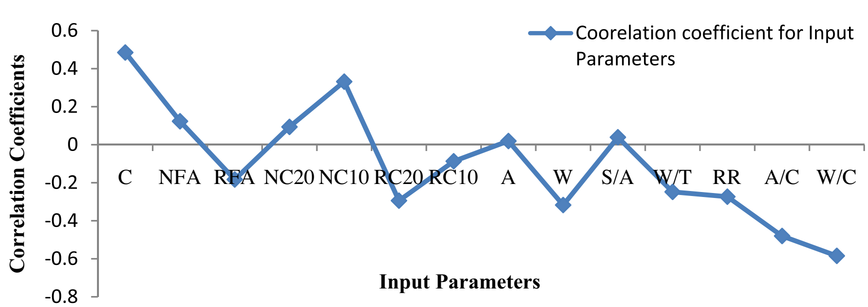

Fig. 1. Correlation coefficients for input parameters.

Table 2
Methodology adopted for Set 1.

Sr. No	Input parameters	ANN Model	Architecture for ANN models	MT Model	NLR Model
1	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A	ANN1	9:28:1	MT1	NLR1
2	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, S/A	ANN2	10:33:1	MT2	NL2
3	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, W/T	ANN3	10:49:1	MT3	NLR3
4	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, RR	ANN4	10:53:1	MT4	NLR4
5	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, A/C	ANN5	10:32:1	MT5	NLR5
6	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, W/C	ANN6	10:36:1	MT6	NLR6

Table 3
Methodology adopted for Set 2.

Sr. No	Input Parameters	ANN Model	Architecture for ANN models	MT Model	NLR Model
1	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, S/A, W/T	ANN7	10:33:1	MT7	NLR7
2	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, S/A, W/T, RR	ANN8	10:49:1	MT8	NLR8
3	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, S/A, W/T, RR, A/C	ANN9	10:53:1	MT9	NLR9
4	C,NFA,RFA,NCA-20,NCA-10, RCA-20, RCA-10, W, A, S/A, W/T, RR, A/C, W/C	ANN10	10:32:1	MT10	NLR10

et al., 1992). For NLR same input/output parameters and data division were used as used for ANN and MT. Input parameters are termed as Independent parameters and Output parameter as dependent parameter for NLR. In NLR models, coefficients (a_0, a_1,...) were determined for Eq. (3) with relevant dependent and independent parameters as discussed in the previous section.

5. Results and discussion

Ten models were developed in the present study as explained in Section 4 using ANN, MT and NLR technique for each model with dimensional and non-dimensional parameters as inputs and 28 day compressive strength as output. The developed models with their respective inputs as discussed above were tested for their performance by means of correlation coefficient (r), Normalized root mean squared error (NRMSE), Average absolute error (AARE) and Nash–Sutcliffe Efficiency (E). The values of the same calculated for each of the models is shown in Table 4 for ANN, in Table 5 for MT and in Table 6 for NLR.

Table 4
Error values for models developed using ANN.

	NRMSE	AARE	E	r
ANN1	0.14	10.9	0.86	0.93
ANN2	0.13	10.50	0.88	0.94
ANN3	0.14	10.19	0.84	0.92
ANN4	0.12	9.67	0.89	0.95
ANN5	0.15	13.08	0.84	0.92
ANN6	0.16	12.97	0.80	0.90
ANN7	0.13	10.73	0.88	0.94
ANN8	0.15	12.53	0.83	0.93
ANN9	0.12	10.33	0.88	0.93
ANN10	0.12	9.31	0.89	0.95

Table 5
Error values for models developed using MT.

	NRMSE	AARE	E	r
MT1	0.19	12.78	0.72	0.85
MT2	0.20	12.97	0.71	0.84
MT3	0.18	12.79	0.75	0.87
MT4	0.2	12.37	0.70	0.84
MT5	0.20	13.37	0.69	0.84
MT6	0.27	22.26	0.46	0.71
MT7	0.18	12.02	0.75	0.87
MT8	0.19	12.75	0.72	0.86
MT9	0.19	13.88	0.71	0.85
MT10	0.22	18.27	0.64	0.80

Table 6
Error values for models developed using NLR.

	NRMSE	AARE	E	R
NLR1	0.21	16.79	0.67	0.82
NLR2	0.19	14.63	0.72	0.85
NLR3	0.2	16.54	0.68	0.82
NLR4	0.21	16.5	0.66	0.81
NLR5	0.21	16.50	0.67	0.82
NLR6	0.2	16.60	0.68	0.82
NLR7	0.19	14.71	0.73	0.86
NLR8	0.20	15.57	0.68	0.83
NLR9	0.20	15.73	0.67	0.82
NLR10	0.19	15.51	0.73	0.86

NLR models were developed in the form of equations with coefficients for each input parameter and constant. The coefficients for the parameters and constants for each model are as shown in Table 7a and b.

Performances of each model developed using the above mentioned techniques were compared. In each of the models developed, models developed using ANN show a better performance than models developed using MT and NLR

Table 7
Coefficients for NLR models.

Model	Constant	C	NFA	RFA	NC20	NC10
(a)						
NLR1	9.24	1.14	0.012	−0.0006	0.002	0.018
NLR2	10.62	1.14	0.010	−0.002	0.002	0.019
NLR3	58697.51	1.20	0.013	−0.0003	0.004	0.015
NLR4	7.75	1.17	0.017	0.010	0.001	0.016
NLR5	42303.28	0.008	0.013	−0.0002	0.005	0.016
NLR6	9.24	0.14	0.012	−0.0006	0.002	0.018
NLR7	43954.71	1.20	0.011	−0.0010	0.004	0.017
NLR8	2409805.53	1.29	0.019	0.0149	0.004	0.011
NLR9	1552575.69	−0.37	0.019	0.0150	0.004	0.011
NLR10	79.97	1.01	1.00	1.00	1.00	1.00

Model No.	Coefficient								
	RCA20	RCA10	A	W	S/A	W/T	RR	A/C	W/C
(b)									
NLR1	−0.003	0.006	0.004	−0.993					
NLR2	−0.003	0.005	0.002	−1.007	0.214				
NLR3	−0.003	0.006	0.003	−2.199	–	1.153			
NLR4	0.005	0.009	0.004	−0.977	–	–	−0.976		
NLR5	−0.003	0.006	0.003	−1.046				−0.945	
NLR6	−0.003	0.006	0.004	−0.0003					−0.993
NLR7	−0.003	0.005	0.0014	−2.155	0.182	1.101			
NLR8	0.010	0.012	0.0006	−2.730	0.182	1.668	−0.025		
NLR9	0.010	0.012	−0.0003	−1.132	−1.316	0.189	0.069	−0.025	
NLR10	1.00	1.00	0.99	0.96	0.24	15091792464	0.998	0.55	2763.36

technique as shown by comparatively high values of r, E and low values of NRMSE and AARE as shown in Tables 4–6. It was seen that with minimum 9 input parameters as shown in Table 1, ANN predicts the strength of concrete better than MT and NLR. With the same 9 mandatory input parameters, it was also seen that MT shows a performance better than NLR. As many as 21 models were developed by MT as linear regression equations (Model MT1) at each node, the coefficients of which show similar influence of input parameters in that cement, natural fine aggregate have positive coefficients and water has negative coefficients, which is in agreement with NLR equations as well (Model NLR1). A typical MT and linear regression equations developed for MT1 are shown in Figs. 2 and 3. The Non-linear Regression equation developed for NLR1 is as shown in Eq. (4) below.

$$S = 9.242 * (C^{1.14}) * (NFA^{0.012})(RFA^{-0.0006}) \times (NC20^{-0.002})(NC10^{0.017})(RC20^{-0.003}) \times (RC10^{0.0054})(A^{0.004})(W^{-0.993}) \quad (4)$$

The models developed using each of the three techniques for set 1 indicates the dominance of ANN over MT and NLR as evident by the model assessment (Tables 4–6). An increases in the accuracy of prediction can be seen in ANN model when (sand by aggregate ratio) S/A and RR (replacement ratio) were added as non-dimensional parameters (model ANN2 and ANN5). Same can be said about

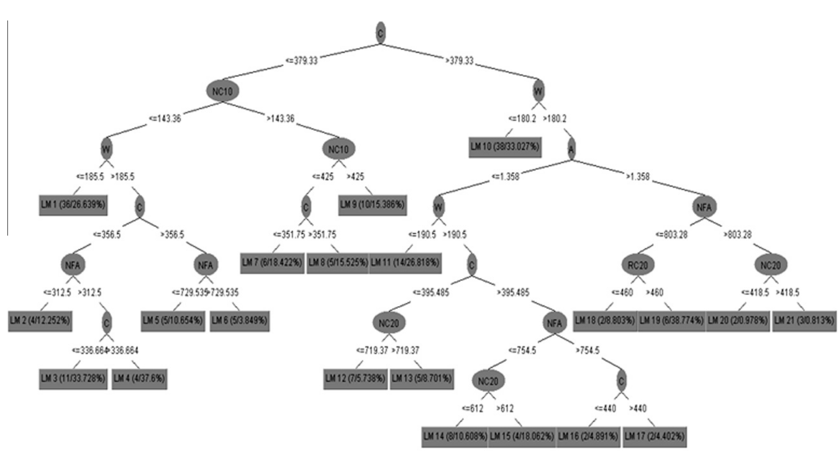

Fig. 2. Model Tree for MT1.

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C <= 379.33 :
|   NC10<= 143.36 :
|   |   W <= 185.5 : LM1 (36/26.639%)
|   |   W > 185.5 :
|   |   |   C <= 356.5 :
|   |   |   |   NFA <= 312.5 : LM2 (4/12.252%)
|   |   |   |   NFA > 312.5 :
|   |   |   |   |   C <= 336.664 : LM3 (11/33.728%)
|   |   |   |   |   C > 336.664 : LM4 (4/37.6%)
|   |   |   C > 356.5 :
|   |   |   |   NFA <= 729.535 : LM5 (5/10.654%)
|   |   |   |   NFA > 729.535 : LM6 (5/3.849%)
|   NC10> 143.36 :
|   |   NC10 <= 425 :
|   |   |   C <= 351.75 : LM7 (6/18.422%)
|   |   |   C > 351.75 : LM8 (5/15.525%)
|   |   NC10 > 425 : LM9 (10/15.386%)
C > 379.33 :
|   W <= 180.2 : LM10 (38/33.027%)
|   W > 180.2 :
|   |   A <= 1.358 :
|   |   |   W <= 190.5 : LM11 (14/26.818%)
|   |   |   W > 190.5 :
|   |   |   |   C <= 395.485 :
|   |   |   |   |   NC20 <= 719.37 : LM12 (7/5.738%)
|   |   |   |   |   NC20 > 719.37 : LM13 (5/8.701%)
|   |   |   |   C > 395.485 :
|   |   |   |   |   NFA <= 754.5 :
|   |   |   |   |   |   NC20 <= 612 : LM14 (8/10.608%)
|   |   |   |   |   |   NC20 > 612 : LM15 (4/18.062%)
|   |   |   |   |   NFA > 754.5 :
|   |   |   |   |   |   C <= 440 : LM16 (2/4.891%)
|   |   |   |   |   |   C > 440 : LM17 (2/4.402%)
|   |   A > 1.358 :
|   |   |   NFA <= 808.28 :
|   |   |   |   RC20 <= 460 : LM18 (2/8.803%)
|   |   |   |   RC20 > 460 : LM19 (6/38.774%)
|   |   |   NFA > 808.28 :
|   |   |   |   NC20 <= 418.5 : LM20 (2/0.978%)
|   |   |   |   NC20 > 418.5 : LM21 (3/0.813%)
```

```
LM num: 1
S = 0.0734 * C + 0.0031 * NFA - 0.009 * RFA - 0.0035 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0041 * RC10 + 0.2661 * A - 0.0295
* W     + 17.8328
LM num: 2
S = 0.0009 * C - 0.0044 * NFA - 0.0168 * RFA - 0.0035 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0041 * RC10 + 0.2661 * A - 0.0295
* W     + 44.4841
LM num: 3
S = -0.0002 * C - 0.0059 * NFA - 0.0168 * RFA - 0.0035 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0041 * RC10 + 0.2661 * A - 0.0295
* W     + 46.5462
LM num: 4
S = 0.0031 * C - 0.0059 * NFA - 0.0168 * RFA - 0.0035 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0041 * RC10 + 0.2661 * A - 0.0295
* W     + 45.8803
LM num: 5
S = -0.0419 * C - 0.0196 * NFA - 0.0207 * RFA - 0.003 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0043 * RC10 + 0.2661 * A - 0.0295
* W     + 66.6685
LM num: 6
S = -0.0419 * C - 0.0196 * NFA - 0.0207 * RFA - 0.0027 * NC20 + 0.0042 * NC10 - 0.005 * RC20 - 0.0041 * RC10 + 0.2661 * A - 0.0295
* W     + 66.0992
LM num: 7
S = 0.1587 * C + 0.1541 * NFA - 0.008 * RFA - 0.0028 * NC20 - 0.0022 * NC10 - 0.0107 * RC20 - 0.0041 * RC10 + 0.5912 * A - 0.0295
* W     - 105.0332
LM num: 8
S = 0.1535 * C + 0.1578 * NFA - 0.008 * RFA - 0.0028 * NC20 - 0.0022 * NC10 - 0.0107 * RC20 - 0.0041 * RC10 + 0.5912 * A - 0.0295
* W     - 106.9457
LM num: 9
S = 0.1351 * C + 0.118 * NFA - 0.008 * RFA - 0.0028 * NC20 - 0.0026 * NC10 - 0.0137 * RC20 - 0.0041 * RC10 + 0.5912 * A - 0.0295 *
W     - 74.449
LM num: 10
S = 0.1146 * C + 0.0082 * NFA - 0.0036 * RFA - 0.0178 * NC20 + 0.0189 * NC10 - 0.0259 * RC20 - 0.0038 * RC10     - 0.2781 * A -
0.2376 * W + 60.0578
LM num: 11
S = 0.0672 * C - 0.0023 * NFA - 0.0036 * RFA - 0.0039 * NC20 + 0.0291 * NC10 - 0.0047 * RC20 - 0.0038 * RC10 - 0.2106 * A - 0.2316
* W + 65.399
LM num: 12
S = 0.0699 * C + 0.0008 * NFA - 0.0036 * RFA + 0.0015 * NC20 + 0.0063 * NC10 - 0.0021 * RC20 - 0.0038 * RC10     - 0.2106 * A -
0.1967 * W + 49.414
LM num: 13
S = 0.0699 * C - 0.0023 * NFA - 0.0036 * RFA + 0.0012 * NC20 + 0.0063 * NC10 - 0.0021 * RC20 - 0.0038 * RC10 - 0.2106 * A -
0.1952 * W + 51.5714
LM num: 14
S = 0.0668 * C - 0.0201 * NFA - 0.0036 * RFA + 0.0019 * NC20 + 0.0063 * NC10 - 0.0016 * RC20 - 0.0038 RC10 - 0.2106 * A - 0.2114
* W     + 70.6149
LM num: 15
S = 0.0668 * C - 0.0201 * NFA - 0.0036 * RFA + 0.0021 * NC20 + 0.0063 * NC10 - 0.0016 * RC20 - 0.0038 * RC10 - 0.2106 * A -
0.2114 * W + 70.7751
LM num: 16
S = 0.0609 * C - 0.0276 * NFA - 0.0036 * RFA + 0.002 * NC20 + 0.0063 * NC10 - 0.0012 * RC20 - 0.0038 * RC10 - 0.2106 * A - 0.2114
* W + 78.1189
LM num: 17
S = 0.0609 * C - 0.0276 * NFA - 0.0036 * RFA + 0.002 * NC20 + 0.0063 * NC10 - 0.0012 * RC20 - 0.0038 * RC10 - 0.2106 * A - 0.2114
* W + 78.0626
LM num: 18
S = 0.0811 * C - 0.0023 * NFA - 0.0036 * RFA - 0.0039 * NC20 + 0.0063 * NC10 - 0.0003 * RC20 - 0.0038 * RC10 - 1.1266 * A - 0.2396
* W + 60.672
LM num: 19
S = 0.0819 * C - 0.0023 * NFA - 0.0036 * RFA - 0.0039 * NC20 + 0.0063 * NC10 - 0.0011 * RC20 - 0.0038 * RC10 - 1.3049 * A - 0.2396
* W + 61.909
LM num: 20
S = 0.0888 * C - 0.0023 * NFA - 0.0036 * RFA - 0.0036 * NC20 + 0.0063 * NC10 - 0.0047 * RC20 - 0.0038 * RC10 - 2.3407 * A - 0.2396
* W + 60.5093

LM num: 21
S = 0.0888 * C - 0.0023 * NFA - 0.0036 * RFA - 0.0036 * NC20 + 0.0063 * NC10 - 0.0047 * RC20 - 0.0038 * RC10 - 2.3407 * A - 0.2396
* W + 60.55
```

Fig. 3. Equations developed for MT1.

MT2 and MT5 model developed with similar inputs though marginally. However though NLR 2 shows a considerable improvement over NLR1, NLR5 shows a similar performance as that of NLR1. A large reduction in prediction accuracy was seen when W and W/C (Water and Water–Cement ratio) became the part of input parameters together in combination for MT model (MT6) with r reduced from 0.87 to 0.71. However for ANN models such a large reduction in model accuracy is not seen (r varies from 0.95 to 0.9). The reduction in model accuracy for MT can be attributed to the duplication of water as data in terms of Water content and Water–Cement ratio. Thus it can said that MT is more sensitive to the data where as ANN is robust. For the same set of input parameters NLR (model NLR6) also does not exhibit much variation in the model accuracy (Table 6).

The influence of various parameters on the compressive strength of RAC can be understood by studying the Hinton diagram. A Hinton diagram (named after Geoff Hinton, who used this type of display to plot the weight matrix of a neural network), where the size of the square represents the magnitude, and the color represents the polarity (red = positive, green = negative). A Hinton diagram thus at a glance shows the units which are strongly active, which input parameters are off and which input parameters are intermediate in influence toward predicting the 28 day compression strength of RAC. A Hinton diagram for ANN1 is shown in Fig. 4 below shows influence of various parameters in ANN1 on the compressive strength of RAC.

It shows the highest influence of water on the compressive strength of RAC which is correct as per principles of concrete technology (Zongjin, 2011; Hong and Ji-Zong, 2000). Thus it can be said ANN cannot be simply declared as black box tools and can be considered as gray boxes. The influence of water by addition of other non-dimensional parameters are though not the highest but very significant as shown by Hinton diagrams of models from ANN 2 to ANN 6 (not shown here). However for MT and NLR models water is associated with a negative coefficient.

As explained earlier, in set 2 compressive strength models were developed by adding non-dimensional parameters one by one in decreasing order of their correlation with the compressive strength. A trend of reduction in performance (Tables 4–6) can be seen here when each non-dimensional parameter was added to the models developed earlier (MT2 and NLR2) except ANN models which show a negligible increase or decrease in the correlation coefficient (r varies between 0.93 and 0.95) This is consistent with earlier observation than ANN is robust compared to MT and NLR.

Fig. 5 shows Hinton diagram for ANN 10 with 14 parameters as it shows the best performance as far as ANN models are concerned.

Here though water is an input parameter along with W/C ratio perhaps the presence of other non-dimensional parameters like S/A, A/C, W/T and RR at one time the performance of ANN 10 model is on the increasing side which showed a decrease when only W and W/C were present as in set 1. Like set 1 MT and NLR models in set 2, show negative coefficients for water content. A positive coefficient was seen for W/T ratio except for NLR10 (Table 7a and b). The Hinton diagram (Fig. 5) confirms

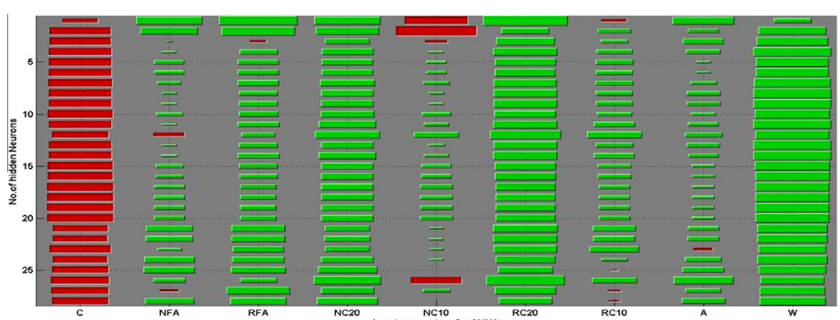

Fig. 4. Hinton diagram for ANN1.

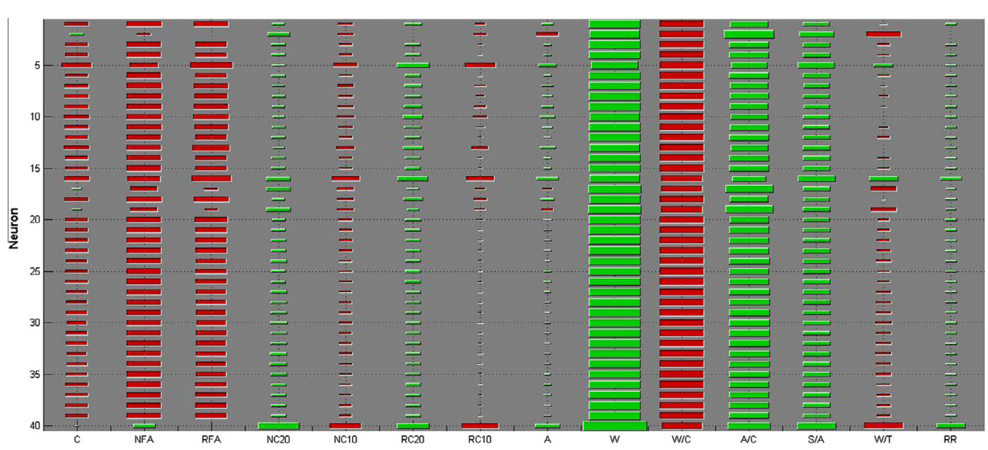

Fig. 5. Hinton diagram for ANN10.

the less emphasis of W/T ratio. For MT a mixed response for W/T ratio was seen in MT10 model which is understandable as MT models are devised at each leaf after dividing the data into different bins.

Fig. 6 compares the predicted 28 day compressive strength of ANN1, MT1, NLR1 with observed values of the same.

The values predicated by ANN1 are much closer to the observed values as compared to MT1 and NLR1. Further model 10, i.e., ANN10, MT10 and NLR10 were selected and graphs were drawn with each input parameter vs compressive strength of concrete for testing values. These graphs can provide an insight into understanding the trend predicting values. Figs. 7–11 show graphs with each input parameter as W/C, A/C, S/A, W/T and RR with 28 day compressive strength of RAC. All the graphs show the similar trend of predicting the output values. In all the graphs at some points under or over predication can be seen. Fig. 12 shows the predicted compressive strength by ANN10, MT10 and NLR 10 models. MT10 and NLR10 tend to over predict at some instances.

With limited number of inputs (mandatory parameters) the performance of ANN (ANN1) model is much better than the model developed using MT(MT1) and NLR (NLR1) technique (Tables 4–6). Additionally ANN has an advantage of learning from the relationships between input and output which is also in tune with the basic knowledge of concrete technology. Use of individual non-dimensional parameters with raw data adds to better performance of ANN. MT, a technique which generates an equation at each node shows better performance than NLR. The divide-and-conquer approach partitions the

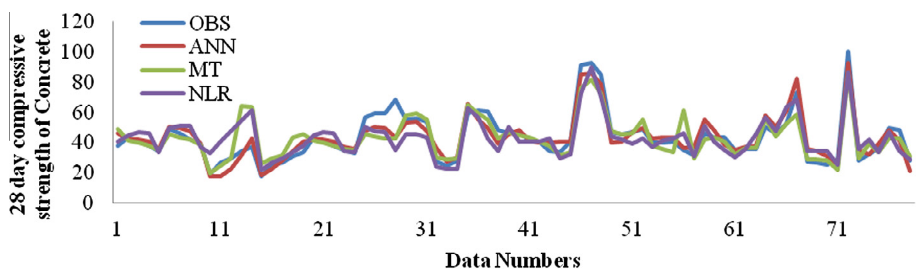

Fig. 6. Comparison of predicated values and observed values for ANN1, MT1 and NLR1.

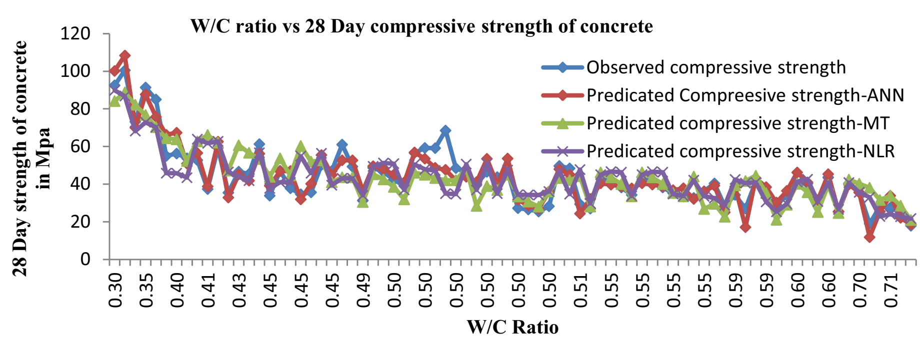

Fig. 7. W/C ratio vs 28 day compressive strength of concrete.

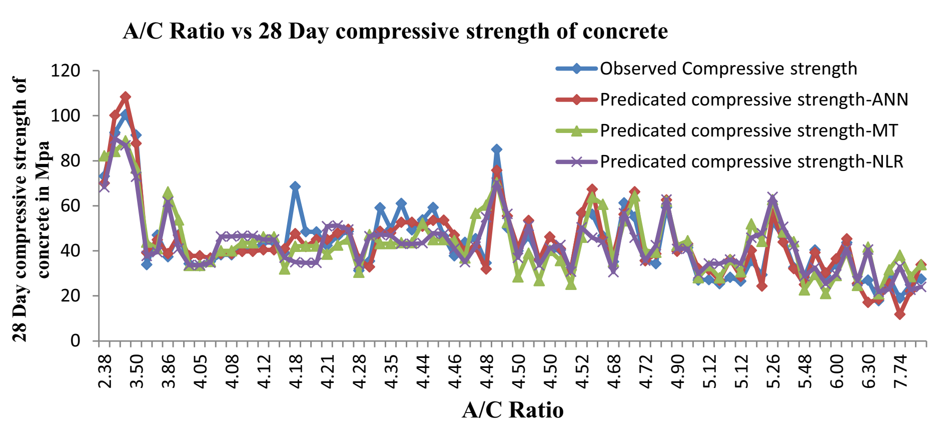

Fig. 8. A/C ratio vs 28 day compressive strength of concrete.

data and provides rules for reaching the models at the leaf nodes and the linear models are then used to quantify the contribution of each attribute to the overall predicted value. This aspect of MT helps in increase of performance of MT as compared to NLR. NLR on the other side though is a technique which can give a ready equation to

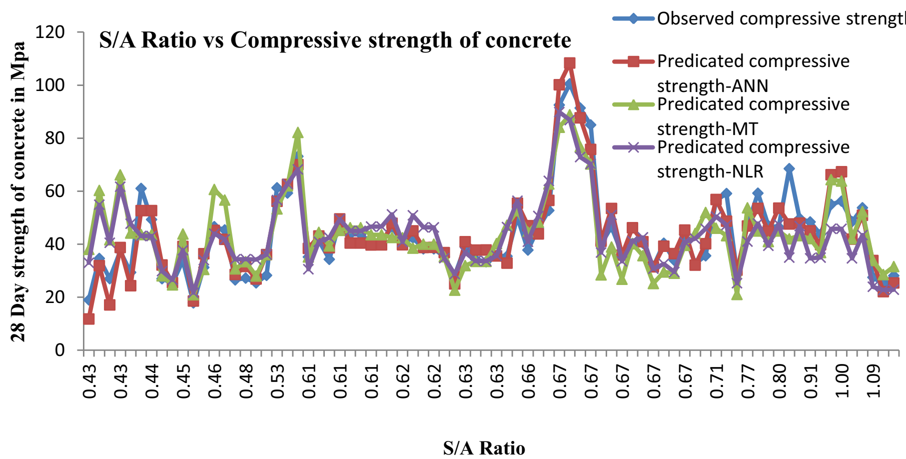

Fig. 9. S/A ratio vs 28 day compressive strength of concrete.

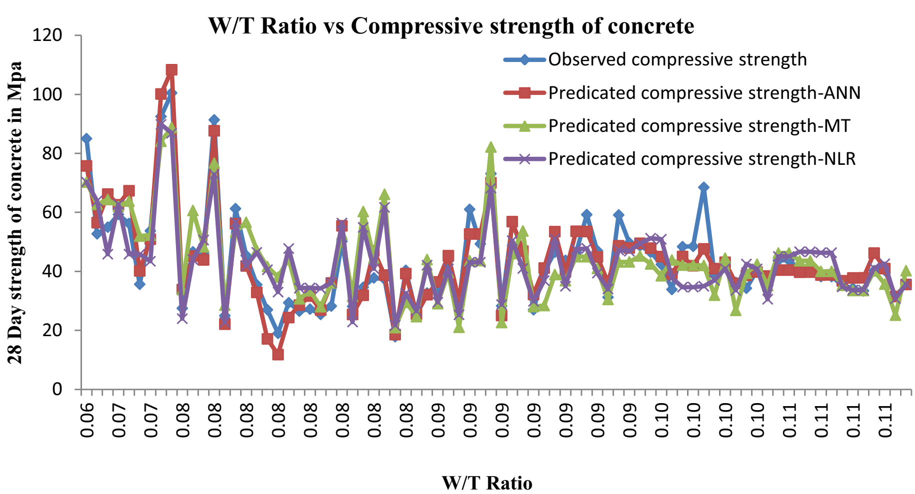

Fig. 10. W/T ratio vs 28 day compressive strength of concrete.

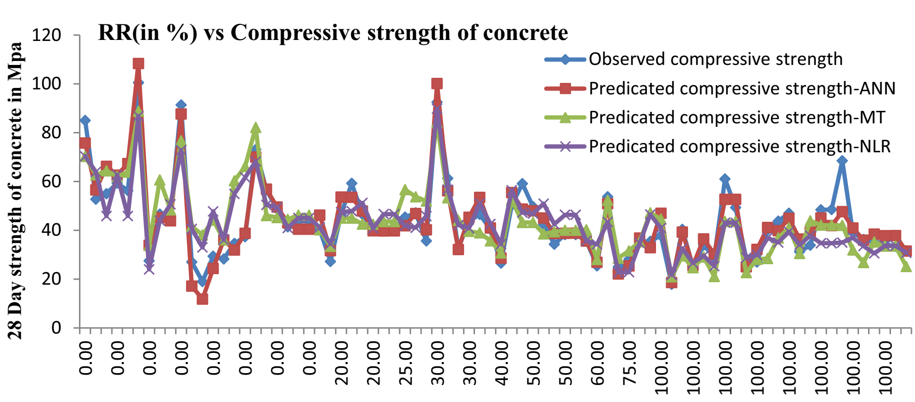

Fig. 11. RR ratio vs 28 day compressive strength of concrete.

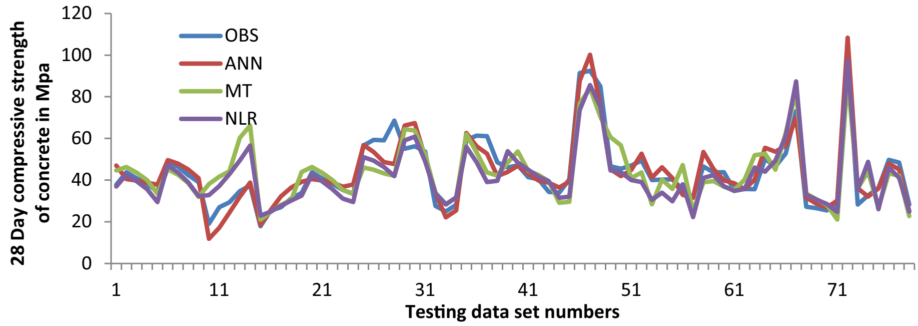

Fig. 12. Comparison of testing values and observed values for ANN10, MT10 and NLR10.

predict the output but its performance is less as compared to ANN and MT. In the second set an attempt was made to check the combined effect of the non-dimensional parameters on performance of mode, which was done in models 7 to 10 by adding each non-dimensional parameter one by one in models. However this may have duplicated the information. This is evident from results of all the three approaches for model Nos. 2 to 10 which are not varying much, indicating that the first model with 9 mandatory parameters is the performing model out of these 10.

6. Conclusions

The paper presented the findings of a study carried out to predict the 28 day compressive strength of concrete using the techniques Artificial Neural Network (ANN), Model Tree (MT) and Non-linear Regression (NLR). The following conclusions can be drawn from this work:

1. Neural networks trained and tested with raw data on proportions of RAC mix contents make better predictions of 28 day compressive strength. Use of non-dimensional parameters as input parameters to develop models may have duplicated the information. This is evident from results of all the three approaches for model Nos. 2 to10 which are not varying much, indicating that the first model with 9 mandatory parameters is the performing model out of these 10.
2. With minimum amount of input parameters (9 mandatory parameters), ANN predicts strength of concrete better than MT and NLR. The trend of prediction is same for all the three techniques in that the over or under predictions are for the same observed values.
3. ANN models dominate over the other techniques in accuracy of predicting the strength of concrete.
4. Models developed using MT technique though shows decreased performance than ANN but has an advantage to build a family of models of varying complexity and accuracy. NLR technique also shows a decreased performance in predicting output than ANN but has an advantage of building a single equation which can be readily used.

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