Modelling Compressive Strength of Recycled Aggregate Concrete Using Neural Networks and Regression

Neela Deshpande[1c], Shreenivas Londhe[2] and Sushama.S.Kulkarni [3]

[1] *Research Scholar,Rajarambapu Institute of Technology,Islampur and A.P,Vishwakarma Institute of Information Technology, Pune, INDIA*
[2]*Professor,Civil Engineering,Vishwakarma Institute of Information Technology,Pune,INDIA*
[3]*Principal,Rajarambapu Institute of Technology,Islampur, INDIA*

Abstract

Recycled aggregates are used in concrete and the concrete is called as Recycled Aggregate Concrete (RAC). This paper aims at predicting the 28 day compressive strength of RAC using two techniques namely Artificial Neural Network (ANN) and Non-linear regression (NLR). Five ANN and NLR models were developed with input parameters as per cubic proportions of cement, sand, natural coarse aggregate, recycled coarse aggregate, water , admixtures used in the mix designs and non-dimensional parameters sand aggregate ratio, water to total materials ratio and the replacement ratio of recycled coarse aggregates to natural aggregates(by volume) in concrete. The effects of each parameter on networks in both techniques were studied. Comparing the techniques shows that ANN performs better than NLR equations. With limited amount of input parameters also, ANN1 predicted the strength of RAC better as compared to NLR1. The performance of ANN models and NLR models improved with the use of non-dimensional parameters.

Keywords: Recycled concrete aggregates; Artificial Neural Networks; Non-linear regression; 28 days Compressive strength; input parameters and non-dimensional parameters.

1. Introduction

Construction and demolition waste (C&D) is increasing day by day and is a cause of concern owing to its harmful effect on the surroundings. A possible solution to these problems is reuse of these C&D waste in concrete. Recycled aggregates (RA) which can be used in concrete as aggregates is a material derived from waste concrete is generally produced by two stage crushing of demolished concrete, screening and removal of contaminants such as reinforcement, wood,

[c] Corresponding Author: Neela Deshpande
Email: deshpandeneela@yahoo.com   Telephone: +91206932300   Fax: +91206932500

plastic etc [1]. Many studies were carried out which prove that concrete made with RA's can have mechanical properties similar to those of conventional concretes and even high strength concrete is nowadays possible [2, 3]. Recycled concrete aggregates (RCA) has mortar and old cement paste attached to it and accounts for 20 to 30% of total volume of aggregates, which increase water absorption capacity and reduces density and becomes governing criteria for the compressive strength of concrete with recycled aggregates [2,4-6]. In a study done using different recycled aggregates (RA) replacement ratios, w/c ratios and RAs with different strengths and different moisture conditions, concluded that the strength of (RAC) was about 10–25% lower than that of Natural aggregate concrete (NAC) and thus 100% replacement of RCA tends to lower the strength of concrete [2,8]. 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 [2]. According to another study made [7] the strength characteristics of recycled aggregate concrete are not affected when w/c ratio is higher. Due to this diverse behaviour of RAC the task of predicting 28th day Compressive strength of RAC becomes tedious and requires both extensive testing and time. A number of efforts were done on using multivariable regression models to improve the accuracy of predictions. In a study, relationships among demolished concrete characteristics, properties of their RA and strength of their RAC were done using regression analysis [9]. An attempt was also made to predict compressive strength of concrete using multiple regressions [10]. The conventional methods for predicting the compressive strength of concrete are based on statistical analysis and involve estimating and the choice of an appropriate regression equation. [11, 17]. ANN has also been a popular technique in predicting the compressive strength of concrete. 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 [12]. ANN is also used to predict the slump flow of concrete [13]. Particularly in the field of RCA, ANN was used to predict strength of recycled aggregate concrete [14].

In the present work five separate models using ANN and NLR equations were developed with various input parameters, some mandatory and remaining non-dimensional parameters made using mandatory parameters, to predict the 28 day compressive strength of RAC. Basic concepts of ANN and NLR equations are described in the next section followed by information about data adopted. The methodology adopted for model development is then presented followed by results and discussion. The conclusions are presented at the end.

2. Artificial neural networks and Non-Linear regression analysis

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 [18].

Multiple linear regressions determine the relationship between two or more independent variables and a dependent variable by fitting a linear equation to 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:

$$Y = a_o + a_1 * X_1 + a_2 * X_2 \ldots .. a_n X_n \tag{Eq.1}$$

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

$$\text{Log } (Y) = \text{Log } (a_o) + a_2 * \log (X_2) + a_3 * \text{Log } (X_3) \ldots\ldots.an * \text{Log}(Xn) \tag{Eq.2}$$

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

$$Y = ao * X1^{a1} * X2^{a2} \ldots\ldots\ldots\ldots\ldots..Xn^{an} \tag{Eq.3}$$

Where   a0, a1, a2…………an   coefficients

        $X_1, X_2, \ldots\ldots\ldots.X_n$ Input 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 [10].

3. Data

The data used in the study was obtained from fresh experimentation done by the authors as well as from the published literature [1-7, 21-39]. Data mainly contained proportions of materials used for making concrete with conventional materials and concrete with RCA. Various parameters used in the study were divided into mandatory parameters and non-dimensional parameters as shown below.

1. Mandatory Input Parameters: As per standard mix design procedures followed all over the world following parameters were treated as mandatory parameters in concrete mix design [15,16].The parameters were Cement (C), Natural fine aggregate (NFA), Recycled fine aggregate (RFA), Natural coarse aggregate-20 mm (NC20), Natural coarse aggregate-10mm (NC10) , Recycled coarse Aggregate20mm(RCA20), Recycled coarse Aggregate-10mm (RCA10), Admixture (A), Water (W) [15,16]. These input parameters remained same for all the networks.

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) were the non-dimensional parameters used derived from the basic mandatory parameters. All the above parameters were termed as Independent variables for NLR.

3. Output parameter or dependent variable: 28 day compressive strength of recycled concrete aggregate.

The maximum and minimum values of input and output parameters are shown in Table 1. A total of 257 data sets are available in which 40 data sets were obtained from fresh experimentation and the remaining from literature.

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

Sr.No	Input Parameters	Range of Values(Min-Max)
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-20mm(NCA-20) Kg/m^3	0-1508.64
5	Natural coarse Aggregates-10mm(NCA-10) Kg/m^3	0-553
6	Recycled Coarse Aggregates-20mm(RCA-20) Kg/m^3	0-1508.64
7	Recycled Coarse Aggregates-10mm(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) Kg/m^3	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

Five different models were developed using ANN and NLR with a common output or dependent variable, of 28th day compressive strength of concrete. The first task was to determine the input parameters or independent variables (except mandatory parameters) for each kind of model which was achieved by correlation analysis between each non-dimensional input parameter or independent variable and the 28 day compressive strength of concrete. Each non-dimensional parameter or independent variable was added with the mandatory parameters according to the decreasing order of their correlation with 28 day compressive strength of concrete. The first network ANN1 and NLR1 contains mandatory parameters as input parameters for ANN1 and the same parameters as independent parameters for NLR1. The second network as well as regression model, ANN2 and NLR2 were having S/A as the first non-dimensional parameter. Subsequently remaining non-dimensional parameters were added, as W/T for ANN3, RR for ANN4 and A/C for ANN5. This allowed us to study the effect of each additional parameter on the performance of network or NLR equations. The networks thus developed are presented in Table 2.

Table 2: Methodology adopted for each Model

Sr. No	Input Parameters	ANN Model	Architecture	NLR Model
1	C,NFA,RFA,NCA-20,NCA-10,RCA-20,RCA-10,W,A	ANN1	9:28:1	NLR1
2	C,NFA,RFA,NCA-20,NCA-10,RCA-20,RCA-10,W,A,S/A	ANN2	10:33:1	NLR2
3	C,NFA,RFA,NCA-20,NCA-10,RCA-20,RCA-10,W,A,S/A,W/T	ANN3	11:66:1	NLR3
4	C,NFA,RFA,NCA-20,NCA-10,RCA-20,RCA-10,W,A,S/A,W/T,A/C	ANN4	12:10:1	NLR4
5	C,NFA,RFA,NCA-20,NCA-10,RCA-20,RCA-10,W,A,S/A,W/T,A/C,RR	ANN5	13:10:1	NLR5

For each model in ANN three layered "Feed forward Back propagation" network was developed to predict the 28 day compressive strength of concrete and trained till a very low performance error (mean squared error) was achieved. The numbers of neurons in hidden layer were decided by trial and error. All the networks were trained using Levernberg-Marquardt algorithm with 'log-sigmoid 'transfer functions in between first (input) and second (hidden) layer and 'linear' transfer function between the second and third layer (output).The data was normalized between 0 to 1. 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) [11, 12, 19, 20]. From the available data 70% of data was used for training, 15% for validation and 15% for testing. In NLR, coefficients (ao, a1…..) were determined for the equation 3 with relevant dependent and independent parameters. The respective model with their respective constants and coefficient for Independent variable C is shown in Table 4.1 and the coefficients for other independent variables for respective models is shown in table 4.2. The data division remained same as in ANN.

5.   Results and discussions

Mix design of concrete typically consists of calculation of proportions of materials used in concrete per cubic meter [15, 16]. As discussed above ANN1 was developed with mandatory parameters as inputs as discussed in the previous section (shown in Table 1). When the trained network was tested for unseen inputs it yielded the coefficient of correlation r of 0.93 between the
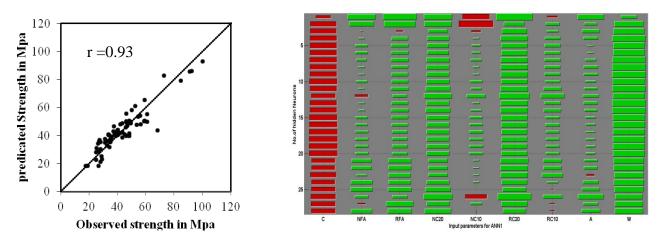
networked predicted and measured compressive strength which is highly satisfactory. The network architecture and correlation coefficients are presented in Table 1 and Table 3 respectively for all the models.

Table 3: Error values for each model

	ANN1	ANN2	ANN3	ANN4	ANN5	NLR1	NLR2	NLR3	NLR4	NLR5
NRMSE	0.14	0.13	0.13	0.13	0.12	0.21	0.20	0.19	0.19	0.21
AARE	10.9	10.50	10.72	11.44	10.33	17.01	14.82	14.91	15.28	15.93
E	0.86	0.88	0.88	0.87	0.89	0.67	0.72	0.73	0.72	0.67
r	0.93	0.94	0.94	0.93	0.94	0.82	0.85	0.86	0.85	0.82

Additionally the statistical measures also exhibited a reasonable performance with low RMSE and AARE values and high value for E as shown in Table 3. The scatter plot for ANN1 is as shown in Fig. 1 which is a balanced one and shows no obvious under or over predictions except at some high values. The Hinton diagram shown in Fig. 2 for ANN1 shows influence of all the input parameters in the form of weight squares between first layer and second layer in which W and C seem to be the most influential followed with aggregates and admixture.
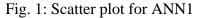

Fig. 1: Scatter plot for ANN1

Fig. 2: Hinton Diagram for ANN1

Table 4: Coefficients for each NLR model

Table 4.1 Constant and Coefficients for C for each NLR model

Model	Constant	C
NLR1	9.24	1.14
NLR2	10.62	1.14
NLR3	43954.70	1.19
NLR4	24001.35	-1.04
NLR5	1552575.70	-0.37

Table 4.2 Coefficients for independent variables for each NLR model

Model	Coefficients											
	NFA	RFA	NC20	NC10	RC20	RC10	A	W	S/A	W/T	A/C	RR
NLR1	0.01	-0.0005	0.0019	0.017	-0.003	0.006	0.004	-0.9929				
NLR2	0.01	-0.0015	0.0018	0.018	-0.003	0.005	0.0018	-1.0063	0.214			
NLR3	0.01	-0.0009	0.0041	0.016	-0.003	0.005	0.0014	-2.1551	0.181	1.1014		
NLR4	0.01	-0.0007	0.0044	0.017	-0.003	0.006	0.0002	0.0117	0.192	-1.0649	-1.779	
NLR5	0.02	0.0150	0.0042	0.012	0.0098	0.012	-0.0003	-1.1315	0.189	0.0689	-1.316	-0.02475

In both the models an increase in r is seen as compared to ANN1 and NLR1 respectively, which highlights the importance of S/A. The S/A coefficient of NLR2, as shown in Table 4 (Table 4.2), also show it as an influential factor after cement.

With the decreasing order of correlation between non-dimensional parameters and compressive strength of RCA concrete, W/T ratio was added as the second non-dimensional parameter in ANN3 and NLR3. Performance of ANN3 is also similar to ANN2 (r = 0.94). Water an important factor for hydration process along with cement affects the strength of concrete. An increase or decrease in water content and w/c for concrete affects the compressive strength of concrete. An increase in W/T results in decrease of concrete strength [15, 16]. With addition of W/T as independent parameter, NLR3 shows an increase in the performance of the model and also highlights the influence of W/T on output by a coefficient of 1.1014.

ANN4 showed a slight decrease in performance than ANN2 and ANN3, with r = 0.93, when A/C ratio was used as the next input parameter. An increase in A/C ratio for a constant w/c ratio gives a leaner mix and leads to higher strength and also leads to lower shrinkage. Thus as A/C ratio, the compressive strength increases [15, 16]. Fig. 3 shows the Hinton diagram for ANN4 which clearly indicates the influence of quantity of water followed by influence of S/A and W/T and then A/C ratio.
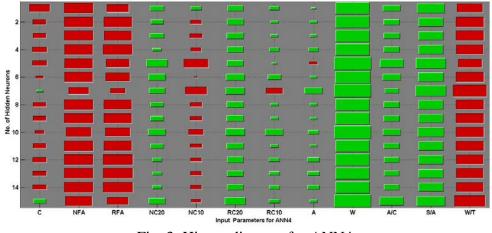

Fig. 3: Hinton diagram for ANN4

However NLR4 showed stronger relation of output with S/A, W/T and A/C respectively by virtue of their coefficients as 0.192,-1.0649 and -1.779, (Refer to Table 4).However NLR4 showed a slight decrease in performance as compared to ANN4. The error measures of NLR4 as shown in

Table 3 confirm the same. RR in % of RCA is an important parameter which contributes towards increase or decrease of compressive strength of concrete. An increase in RCA replacement ratio exhibits a decrease in the recycled aggregate concrete strength due to the weaker properties of RCA as compared to NCA as shown by respective studies [1-7]. With RR as an additional input parameter ANN5 showed r as 0.94. Thus RR ratio holds the fort as an important parameter with same correlation coefficient. However with the same independent parameters, NLR5 shows a negative influence of RR on output with an r =0.82. Fig. 4 compares the 28 days compressive strength of ANN1, NLR1 and observed values of the output.
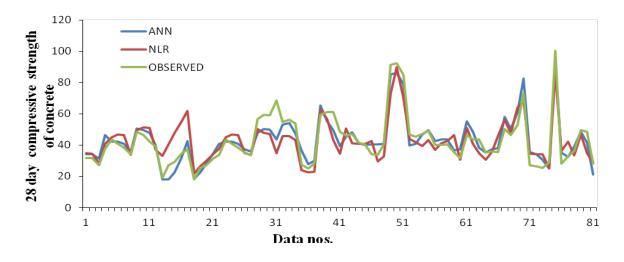

Fig. 4: Comparison of testing values and observed values for ANN1 and NLR1

    The graph clearly indicates that ANN results outsmarted NLR results and much closer to the actual observations. However a poor estimation i.e. over prediction of the output is seen by NLR for the data points 13-19 which has strength range from 19 to 37 N/mm^2. An under prediction can also be seen for data nos. 28-33 by both ANN and NLR. A similar trend can be observed in Fig.5 for ANN5, NLR and observed values.
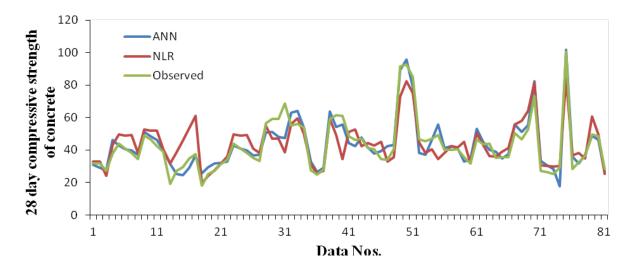

Fig. 5: Comparison of testing values and observed values for ANN5 and NLR5

However in both the cases ANN has a good potential for predicting exact values as compared to NLR for the same objective.

   The above study indicated that ANN is not merely a black box but it understands the physics of the underlying phenomenon as shown by the study conducted [11, 12]. Thus it may be noted that use of dimensionless parameters used in the study derived from the mandatory parameters, can increase (or maintain constant) the performance of the network and thus can predict the 28 day compressive strength of concrete better than other networks which are presented in the current study. It can also be seen that with limited number of inputs also (mandatory parameters) the performance of ANN model is by no means inferior. Non-Linear regression analysis is also a promising technique for modelling the 28 day compressive strength of RAC. However a large data range and decrease of correlation coefficient for the same data set as ANN, makes NLR a less sought after technique for modelling.

6. Conclusions

   RAC is a highly complex material and modelling its behaviour is a difficult task. Artificial Neural networks are capable of learning and generalizing from examples and experiences. In the present study five separate models were developed using ANN and NLR as a tools for predicting 28 day compressive strength of RAC. ANN1 with all 9 mandatory parameters as input parameters showed a satisfactory performance in predicting the 28 day compressive strength of concrete (r =0.93). However for the same data NLR shows an accuracy of 81%. Uses of non dimension parameters like S/A, W/C, A/C, T/W and RR contributed towards equal (if not better) performance of Neural Network models and NLR too. This can be from the increase of r from ANN1 to ANN5 expect ANN4, which showed a slight decrease in r. NLR on the other hand performs better with increase of each non-dimensional parameter as independent parameter from NLR 2 to NLR 4.However NLR5 shows a slight decrease in r when RR was added as a independent parameter. However when all the ANN networks were compared with respective NLR models, performance of ANN is much better than NLR. The Hinton diagrams highlighted the influence of each parameter on the compressive strength by virtue of the weights which are in agreement with the theoretical knowledge.

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