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Prediction of Concrete Properties Using Multiple Linear Regression and Artificial Neural Network

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ABSTRACT

The selection of appropriate type and grade of concrete for a particular application is the critical step in any construction project. Workability and compressive strength are the two significant parameters that need special attention. This study aims to predict the slump along with 7-days & 28-days compressive strength based on the data collected from various RMC plants. There are many studies reported in general to address this issue from time to time over a long period. However, considering the worldwide use of a huge quantity of concrete for various infrastructure projects, there is a scope for the study that leads to most accurate estimate. Here, data from various concrete mixing plants and ongoing construction sites was collected for M20, M25, M30, M35, M40, M45, M50, M55, M60 and M70 grade of concrete. Multiple Linear Regression (MLR) and Artificial Neural Network (ANN) models were built to predict slump as well as 7-days and 28-days compressive strength. A variety of experiments was carried out that suggests ANN performs better and yields more accurate prediction compared to MLR model for both slump & compressive strength.

1. Introduction

Concrete is a composite construction material made up of cement, fine aggregate, coarse aggregate with the addition of a permissible quantity of water and some admixture. It provides

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several advantages regarding strength, durability, versatility, economy, and life of structure [1]. For the maximum strength of any proper structure mix, compaction, curing of concrete is a prime necessity. Workability is the property of concrete which determines the efforts required for placing, compaction and finishing with the minimum loss of homogeneity. On large construction sites for mass concreting, quick determination of essentially the concrete strength and quality properties plays a significant role. The search of various methods and prediction tools to find the required slump and compressive strength has been the subject of research for many decades. The major aim of such methods is to ease the process of determination of concrete properties while maintaining cost-effective material, its workability, life, etc. Numerous researchers have applied soft and hard computing methods for prediction of the variety of parameters related to concrete mix and their properties in general. Some studies for concrete containing various combinations of materials such as nano-silica and copper slag have been carried out [2]. One of the traditional methods used to predict compressive strength is Multiple Linear Regression (MLR) [3]. In recent past, the soft computing tool such as Artificial Neural Network (ANN) was employed to solve complex non-linear problems with the help of highly interconnected neurons. ANN tends to exploit non-linearity and predict input-output relationship in a better manner [4,5].

28 days compressive strength prediction of concrete using soft tools like ANN, Fuzzy Logic (FL) and Adaptive Neuro-Fuzzy Inference System (ANFIS) was also reported [6–9]. The three different data-driven models, i.e., ANN, ANFIS, and MLR were used to predict 28 days compressive strength of recycled aggregate concrete (RAC). It was observed that the prediction made by ANN & ANFIS models was good in comparison with MLR [10,11]. Khademi et al. suggested MLR for preliminary mix design of concrete, and ANN for mix design offers higher accuracy [12]. A mathematical model for the prediction of Portland cement compressive strength after 2, 7 and 28 days was developed based on regression analysis. It was found to offer satisfactory accuracy [13]. However, the evaluations were related to few parameters. Similar results were obtained for steel fiber added lightweight concrete using ANN [14]. Mansour et al. predicted shear strength of reinforced concrete beams by employing ANN [15]. ANN is also exploited for predicting elastic modulus of normal and high strength concrete within the range of input parameters [16]. It is seen that in general ANN models were commonly used to predict various parameters along with MLR. Non-destructive prediction of concrete was carried by Adnan et al. [17]. Compressive strength prediction for high-performance concrete was carried using ANN [18]. Similar ANN based studies with little changes in parameters used and their combinations can be found in [19,20].

Many researchers have used the combination of various data for modeling parameters, but only a few researchers have used specific grade concrete data for modeling. It is known that concrete is characterized by its grade for specific purpose infrastructure or types of work. The grade of concrete to be used for a particular work is based on the type of work. The main objective of this study was to predict slump as well as 7 and 28 days compressive strength of various grades of concrete such as M20, M25, M30, M35, M40, M45, M50, M60, and M70. The solution was aimed at predicting values separately for each grade of concrete required for the specific purpose. Further, this study also aimed at finding 7 and 28 days concrete strength.

2. Data collection and methodology

2.1. Data collection

Nowadays, for speedy work and reliable concrete mixes, Ready Mix Concrete (RMC) plants serve better choice, and it is an integral part of the construction industry. The data used was collected from RMC plants located around Mumbai, Navi Mumbai, and Raigad district of Maharashtra State, India, where large construction activities are always going on. The data of mix and testing results on site about various grades of concrete ranging from M20 to M70 was collected from five different sites at the above-mentioned locations. These sites were selected from reputed companies catering to the large geographical area and which are constantly in high demand since Mumbai, Navi Mumbai and suburbs have large developing pockets.

Data were collected for the year 2016- 2017 and includes cement quantity (C), fly ash (F), Ground Granulated Blast Furnace Slag (GGBS), Fine Aggregate quantity (FA), a coarse aggregate of size 10mm (CA10), 20mm (CA20), Water quantity (W) and Super Plasticizer dosage (SP) with slump and 7, 28 days compressive strength details of various grades of concrete respectively. Table 1 gives the sample of characteristics for an M40 grade of concrete. Similarly, characteristics are studied and analyzed for all the grades of concrete.

2.2. Methodology

The database was analyzed and separated according to the grades and input-output parameters to verify suitability in formulating the prediction model. To avoid complexity during modeling, ingredients that play important role for concrete mix preparation like cement, fine aggregate, a coarse aggregate of 10mm and 20mm size, and water content were considered. The predicted parameters were slump, 7 days and 28 days compressive strength of the mix of concrete grades.

Table 1
Characteristics of the M40 grade of concrete (sample).

Parameters	Units	Minimum	Maximum	Standard Deviation	Mean
Cement	Kg/m^3	300	450	40.62	391.00
Fine aggregate	Kg/m^3	660	988	82.75	841.20
10 mm size aggregate	Kg/m^3	301	592	72.45	384.03
20 mm size aggregate	Kg/m^3	500	830	67.41	603.83
Water	Kg/m^3	102	211	23.94	163.00
Slump	mm	100	600	120.95	220
7-days compressive strength	N/mm^2	22.21	40.98	5.81	35.60
28-days compressive strength	N/mm^2	40.15	55.64	5.57	50.89

The first model was built using MLR that estimates the level of correlation between one dependent variable (output variable) from two or more independent variables (input variables). It explores a correlation regarding a straight line that best predicts all the individual data points containing both target and output variables. The details of MLR can be obtained based on the values of correlation coefficient (r), determination coefficient (R^2), p-value, and F-test. The general form of MLR model is,

$$\hat{Y} = a_0 + a_1 * (X_1) + a_2 *(X_2) + a_3 *(X_3) + a_4*(X_4) + a_5 *(X_5)....+ a_n*(X_n) \quad (1)$$

where $\hat{Y}$ is the model's output, $X_1, X_2, X_3, X_4, X_5.....X_n$ are independent input variables of the model, and $a_0, a_1, a_2, ..., a_n$ are the partial regression coefficients.

In this study, MLR models have been built for various concrete grades. The best MLR model as a sample equation, which has the most correlation with slump & compressive strength of concrete, is given in equation (2), (3) & (4),

- Slump = 887.92- (0.19 x C)- (0.19 x FA)- (0.39 x CA10)- (0.43 x CA20) - (0.30 x W) (2)
- 7days compressive strength = 202.75 + (0.03 x C) - (0.11 x FA) - (0.10 x CA10) - (0.05 x CA20) - (0.06 x W) (3)
- 28 days compressive strength = 162.72+ (0.04 x C) - (0.08 x FA) - (0.05 x CA10)- (0.03 x CA20) - (0.11 x W) (4)

Table 2 exhibits MLR coefficients for 28 days compressive strength for grade M20. Standard error, P-value & t-stat are known as a measure of accuracy for calculating the regression coefficient. These metrics are found and sample values are depicted in Table 2. P-value of 5% or less is the generally accepted value and suggest acceptable regression model. As can be seen from Table 2, lees value of error and desired range of P values suggests built regression model is acceptable. Similarly, concrete grade equations were obtained and analysed for M25, M30, M35, M40, M45, M50, M60 and M70 for predicting slump as well as 7 & 28 days compressive strength.

Table 2
MLR coefficients for the 28-day compressive strength of M20 grade.

Predictor	Variables	Coefficient	Standard Error	P Value	t-statistic
Constant	Constant	162.72	39.12	0.0002	4.15
Cement	C	0.040	0.016	0.023	2.38
Fine aggregate	FA	-0.085	0.026	0.002	-3.26
Coarse aggregate 10mm	CA10	-0.052	0.024	0.039	-2.14
Coarse aggregate 20mm	CA20	-0.028	0.013	0.049	-2.04
Water	W	-0.112	0.054	0.046	-2.07

Prediction of slump and compressive strength was also carried out using artificial neural networks. They are simplified models of the biological nervous system and are highly interconnected networks of a large number of processing elements called neurons in an architecture inspired by a brain. ANN consists of the input layer, an output layer and one or more hidden layers which are interlinked by many weights.

In the present work, Generalized Feed Forward Networks (GFFN) was used to estimate the slump as well as 7 and 28 days compressive strength for various concrete grades. The data division and the input-output parameters used in MLR have been kept same in ANN modeling. The schematic view of proposed ANN architecture is shown in Fig. 1.

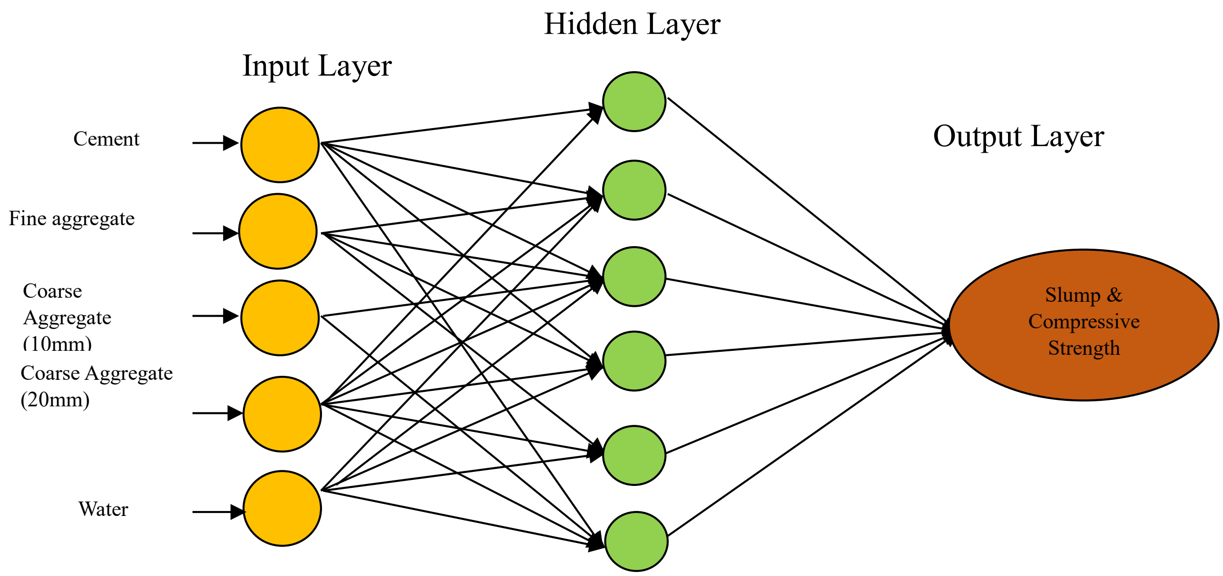


Fig. 1. General Architecture of ANN.

Various transfer functions such as Linear TanhAxon, TanhAxon, LinearAxon, SigmoidAxon and learning rules like Momentum, Levenberg-Marquardt, Conjugate Gradient, Delta Bar Delta and Quick prop were used to arrive at best results. SigmoidAxon function often used in ANN introduces non-linearity in the model and captures high and low values well. It was observed that SigmoidAxon as a transfer function and Levenberg Marquardt as learning algorithm had given a better prediction. The processing structure of the network is shown in Fig. 2. Simulation results were obtained using Neurosolutions V5 platform.

The quantitative performance of MLR and ANN models was judged by the correlation coefficient (r), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Normalized Mean Square Error (NMSE). Here, the aim was to judge the model performance in all the situations with a maximum number of error measures. It is to be also noted that sometimes the values of correlation coefficient alone cannot provide the accuracy and insights of the prediction models. The qualitative analysis was carried out with the help of scatter plots.

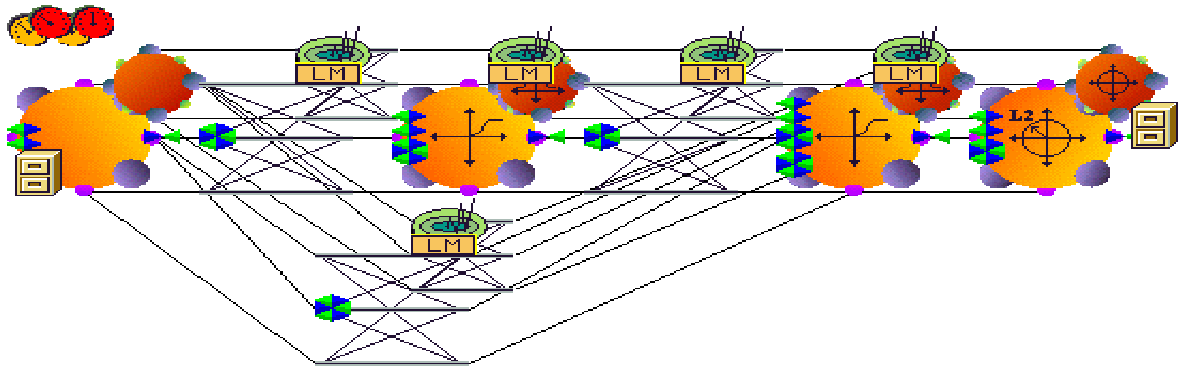


Fig. 2. M20 grade concrete ANN model.

3. Results and discussion

Accurate prediction of 7 and 28 days strength is important nowadays considering the need for fast progress of any infrastructure project. The main aim of this study was to predict slump and the compressive strength for 7 and 28 days. MLR and ANN models were built using the data collected. Various combinations of data division were used to arrive at the maximum accuracy regarding correlation coefficient and error measures and also regarding qualitative analysis by scatter plots. Combinations like 60%–40%, 70%–30%, 75%–25%, and 80%–20%, i.e. division of data in model building and model testing were employed to build models for slump as well as 7 days and 28 days compressive strength. After all the trials, it was observed that 80%-20% (training- testing) data division offered maximum accuracy for both MLR and ANN in all grades of concrete mentioned. In both models, data division to train and test model was kept similar. This was done to compare the performance of the models on the similar ground. Also, it is to be noted that in the model building with 80% data, all the values which affect the outcomes automatically helped in developing the robust model. The developed models were tested on the remaining 20% unseen values for prediction of slump, 7 days and 28 days compressive strength.

It has been found that MLR model predicted values with less accuracy in terms of correlation coefficient which ranges from 0.60 to 0.80 largely. The lower correlation and high error is due to MLR's capability of finding difficulty in understanding the non-linear relationship. Hence, to understand the nonlinear relationship, ANN models were built on the database to predict the 7days & 28 days compressive strength and found to be more accurate.

Fig 3 shows a scatter plot of observed and predicted values by ANN model for 28 days for an M50 grade of concrete. It is found to lie in the best fit zone.

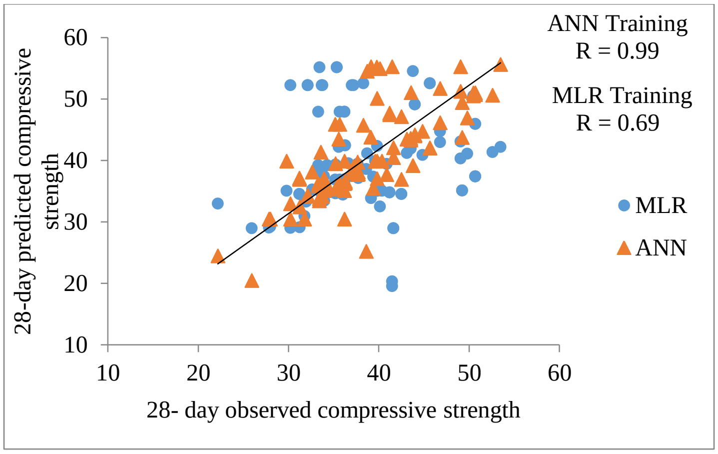


Fig. 3. Comparison of the observed versus predicted values for the training of M50 grade of concrete for 28 days strength.

Similarly, the models were developed for slump as well as 7 days and 28 days of strength for all grades of concretes. Simulation results obtained regarding performance metrics are shown in Fig 3. It was observed that ANN predicted excellent values for slump for almost all the grades of concrete with maximum correlation and fewer errors. The MLR model has high errors and less correlation coefficient, especially in case of M40 and M70. Fig 4 shows good agreement of predicted and observed values of slump for an M50 grade of concrete.

Table 3
Comparison of MLR & ANN model testing results for the slump.

Grades	**Model**	**Slump**			
		R	RMSE	MAE	NMSE
M20	MLR	0.79	38.81	24.58	0.57
	ANN	0.99	09.91	05.38	0.02
M25	MLR	0.71	47.18	65.59	1.13
	ANN	0.99	07.97	03.44	0.01
M35	MLR	0.86	48.85	47.79	0.36
	ANN	0.99	11.65	07.48	0.01
M40	MLR	0.76	50.77	148.46	4.57
	ANN	0.99	04.21	02.85	0.003
M45	MLR	0.82	45.90	72.94	0.85
	ANN	0.99	07.77	05.14	0.003
M50	MLR	0.64	39.37	26.45	2.84
	ANN	0.99	00.82	00.22	0.002
M70	MLR	0.75	55.19	161.38	3.05
	ANN	0.99	15.60	09.76	0.01

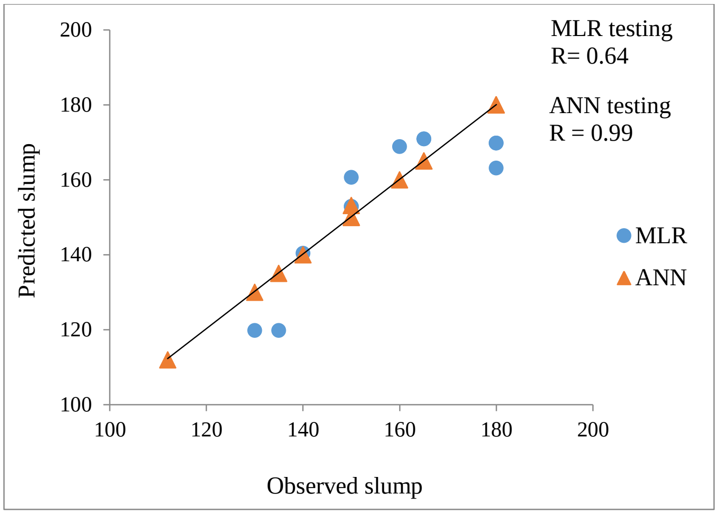
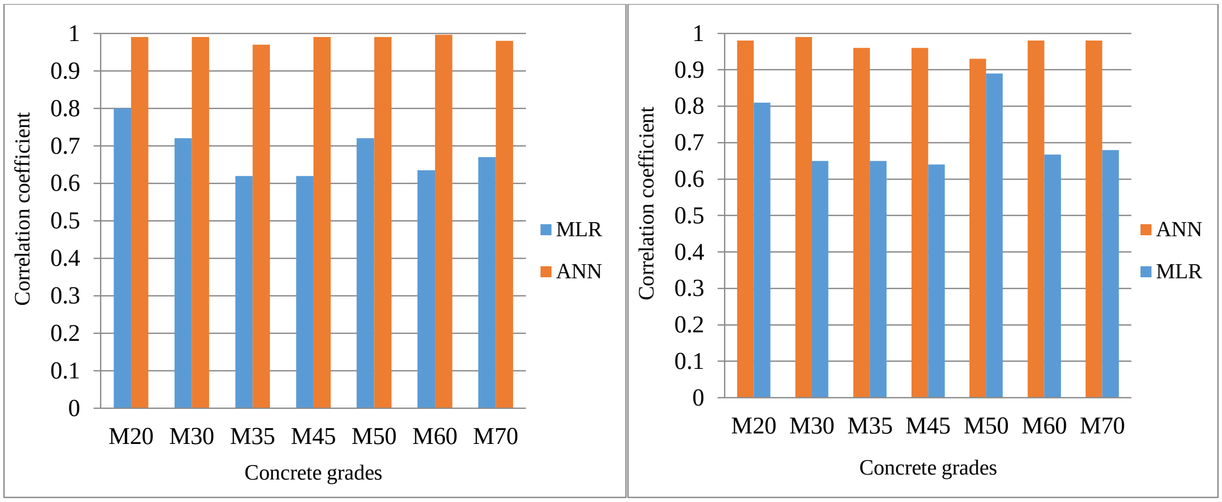


Fig. 4. Comparison of observed Vs predicted slump of M50 grade of concrete in testing.

The results obtained using MLR and ANN models for 7, and 28 days compressive strength are shown in Table 4. It is evident that correlation coefficient values are approaching 1, i.e. ideal value in most of the cases for ANN. Also, error metrics have low values in ANN that suggest the better ability of ANN to predict as compared to MLR. The comparison of the correlation coefficient regarding qualitative analysis for 7 and 28 days compressive strength of concrete is shown in Fig 5 (a,b) that shows values close to 1 for all grades of concrete.

Table 4
Comparison of MLR and ANN model results for 7 and 28-days compressive strength.

Grades	Model	7 days compressive strength				28 days compressive strength			
		R	RMSE	MAE	NMSE	R	RMSE	MAE	NMSE
M20	MLR	0.80	5.32	1.08	0.60	0.81	5.59	2.23	0.58
	ANN	0.99	1.69	0.59	0.03	0.98	1.95	1.04	0.04
M30	MLR	0.72	3.50	2.37	1.68	0.65	5.28	4.19	2.34
	ANN	0.99	0.52	0.19	0.02	0.99	0.27	0.10	0.01
M35	MLR	0.62	5.08	3.77	3.01	0.65	5.59	4.21	2.40
	ANN	0.97	0.94	0.63	0.06	0.96	1.16	0.64	0.08
M40	MLR	0.65	6.24	5.03	1.79	0.73	6.77	5.75	1.85
	ANN	0.92	1.20	0.75	0.15	0.96	0.88	0.56	0.09
M45	MLR	0.62	4.81	3.51	4.60	0.64	4.79	4.46	5.78
	ANN	0.99	0.39	0.12	0.02	0.96	0.82	0.51	0.08
M50	MLR	0.72	4.20	2.86	2.16	0.75	7.48	6.12	1.67
	ANN	0.99	0.44	0.22	0.02	0.93	1.18	0.58	0.16
M70	MLR	0.67	8.13	5.30	4.36	0.68	4.53	3.20	4.82
	ANN	0.98	1.53	0.58	0.06	0.98	1.18	0.49	0.07

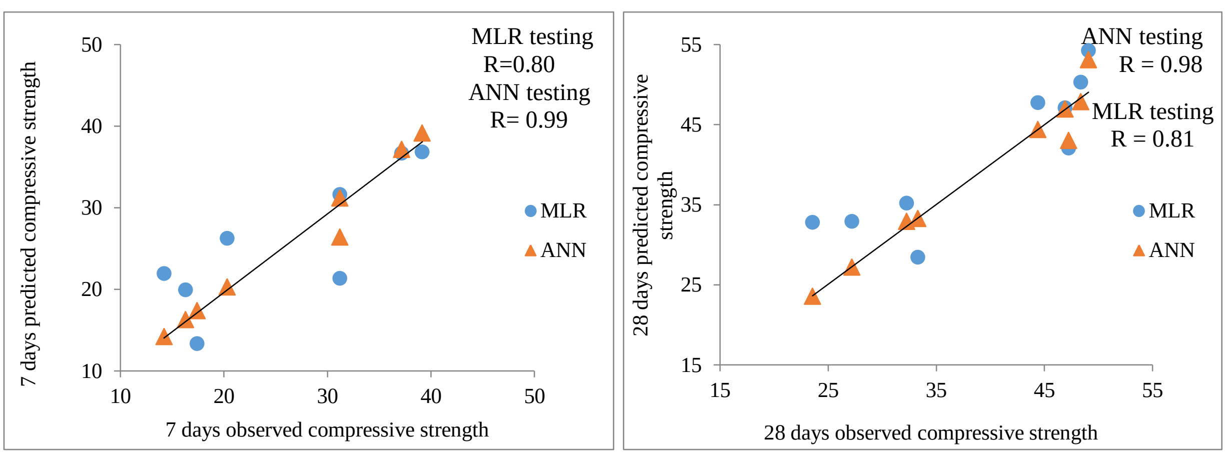


a) 7days compressive strength b) 28days compressive strength

Fig. 5. (a-b) Comparison of coefficient of correlation between MLR and ANN models in testing.

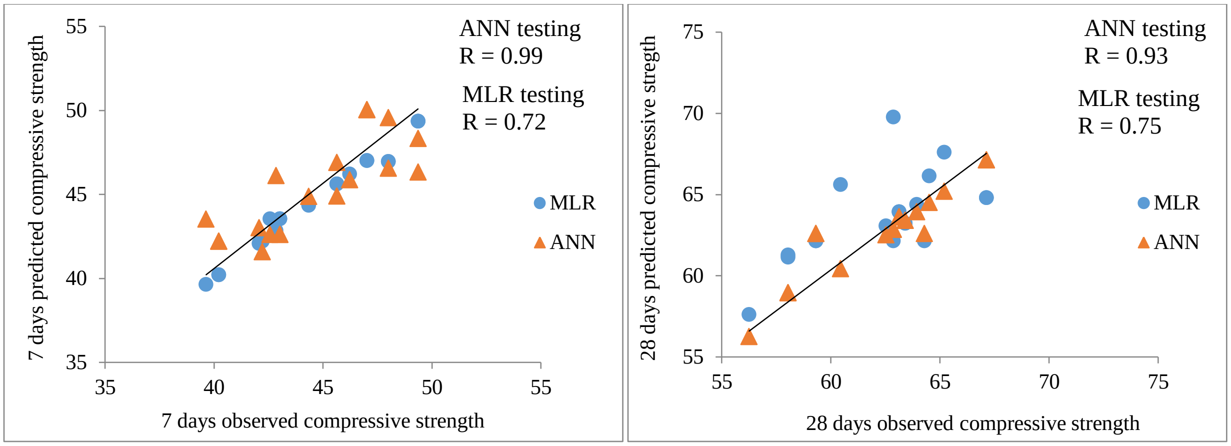
The qualitative analysis in terms of scatter plots between predicted and observed compressive strength is shown in Fig. 6 (a,b) and Fig 7 (a,b) for M20 and M50 grade respectively. It can be seen that maximum values are falling near the best fit.

A similar procedure was adopted for all other grades like M25, M30, M35, M45, M60, and M70. The qualitative and quantitative analysis shows that ANN models developed for all concrete grades showed a high correlation coefficient and low errors as compared MLR models. The values of RMSE and MAE are very low in all the grades compared with MLR. This shows that the nonlinearity of the values is captured well by the ANN models in a verity of mix grades.



a) 7days compressive strength b) 28days compressive strength

Fig. 6. (a-b) Comparison of predicted Vs observed values of M20 concrete grade in testing.



a) 7 days compressive strength b) 28 days compressive strength

Fig. 7. (a-b) Comparison of predicted vs. observed values of the M50 concrete grade in testing

In this study, an attempt was made to quantify predictions for different grades of concrete individually rather than the combination of grades as observed in the literature [21–26]. The correlation coefficient obtained from ANN for M60 and M70 grade of concrete for 28 days compressive strength was 0.98 & 0.99 which is better than the results obtained by the other researchers [25,27,28].

4. Conclusions

This work focuses on the prediction of slump and 7, 28 days compressive strength of concrete which plays an important role during mass construction work. Parameters like cement, fine aggregate, the coarse aggregate of size 10mm, 20mm and water were used to predict the slump and 7 and 28 days compressive strength. MLR and ANN models were developed for M20 to M70 grade of concrete based on the data obtained from RMCs. The models were tested on the unseen values where it was observed that ANN models constantly performed well for all grades of concrete and outperformed MLR in such a set of grades of concrete. Since the analysis was pertaining to the data of RMC plants where transportation is also a key factor, the attempt was made to predict the accurate values of slump and 7 days, and 28 days strength for further assessment since the quality of strength is important to be obtained using such methods. The ANN models could be used in such processes for effective use of concrete.

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